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A SPATIAL IMAGE PROCESSOR

TO ALL WHOM IT MAY CONCERN:

BE IT KNOWN THAT ROGER L. WOODALL, citizen of the United States of America, employee of the United States Government, and resident of Jewett City, County of New London, State of Connecticut, has invented certain new and useful improvements entitled as set forth above, of which the following is a specification.

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1 Attorney Docket No. 77346

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A SPATIAL IMAGE PROCESSOR

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STATEMENT OF GOVERNMENT INTEREST

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The invention described herein may be manufactured and used by and for the Government of the United States of America for governmental purposes without the payment of royalties thereon or therefore.

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CROSS-REFERENCE TO RELATED APPLICATIONS

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This patent application is co-pending with related patent applications entitled NEURAL DIRECTORS (U.S. Patent Application Ser. No. 09/436,957), NEURAL SENSORS (U.S. Patent Application Ser. No. 09/436,956), STATIC MEMORY PROCESSOR (U.S. Patent Application Ser. No. 09/477,638), DYNAMIC MEMORY PROCESSOR (U.S. Patent Application Ser. No. 09/477,653) and MULTIMODE INVARIANT PROCESSOR (U.S. Patent Application Ser. No. 09/641,395), by the same inventor as this patent application.

21

BACKGROUND OF THE INVENTION

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(1) Field of the Invention

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The invention relates to neural networks and is directed more particularly to a spatial image processor neural network for processing spatial image data to distinguish one configuration of component objects from a different configuration of the same component objects.

1 (2) Description of the Prior Art

2 Electronic neural networks have been developed to rapidly
3 identify patterns in certain types of input data, or to classify
4 accurately the input patterns into one of a plurality of
5 predetermined classifications. For example, neural networks have
6 been developed which can recognize and identify patterns, such as
7 the identification of hand-written alphanumeric characters, in
8 response to input data constituting the pattern of on/off picture
9 elements, or "pixels," representing the images of the characters
10 to be identified. In such a neural network, the pixel pattern is
11 represented by, for example, electrical signals coupled to a
12 plurality of input terminals, which, in turn, are connected to a
13 number of processing nodes, each of which is associated with one
14 of the alphanumeric characters which the neural network can
15 identify. The input signals from the input terminals are coupled
16 to the processing nodes through certain weighting functions, and
17 each processing node generates an output signal which represents
18 a value that is a non-linear function of the pattern of weighted
19 input signals applied thereto. Based on the values of the
20 weighted pattern of input signals from the input terminals, if
21 the input signals represent a character, which can be identified
22 by the neural network, one of the processing nodes, which is
23 associated with that character will generate a positive output
24 signal, and the others will not. On the other hand, if the input
25 signals do not represent a character, which can be identified by
26 the neural network, none of the processing nodes will generate a
27 positive output signal. Neural networks have been developed

1 which can perform similar pattern recognition in a number of
2 diverse areas.

3 The particular patterns that the neural network can identify
4 depend on the weighting functions and the particular connections
5 of the input terminals to the processing nodes. As an example,
6 the weighting functions in the above-described character
7 recognition neural network essentially will represent the pixel
8 patterns that define each particular character. Typically, each
9 processing node will perform a summation operation in connection
10 with values representing the weighted input signals provided
11 thereto, to generate a sum that represents the likelihood that
12 the character to be identified is the character associated with
13 that processing node. The processing node then applies the non-
14 linear function to that sum to generate a positive output signal
15 if the sum is, for example, above a predetermined threshold
16 value. Conventional nonlinear functions which processing nodes
17 may use in connection with the sum of weighted input signals
18 generally include a step function, a threshold function, or a
19 sigmoid. In all cases the output signal from the processing node
20 will approach the same positive output signal asymptotically.

21 Before a neural network can be useful, the weighting
22 functions for each of the respective input signals must be
23 established. In some cases, the weighting functions can be
24 established a priori. Normally, however, a neural network goes
25 through a training phase in which input signals representing a
26 number of training patterns for the types of items to be
27 classified (e.g., the pixel patterns of the various hand-written

1 characters in the character-recognition example) are applied to
2 the input terminals, and the output signals from the processing
3 nodes are tested. Based on the pattern of output signals from
4 the processing nodes for each training example, the weighting
5 functions are adjusted over a number of trials. After being
6 trained, the neural network can generally accurately recognize
7 patterns during an operational phase, with the degree of success
8 based in part on the number of training patterns applied to the
9 neural network during the training stage, and the degree of
10 dissimilarity between patterns to be identified. Such a neural
11 network can also typically identify patterns that are similar,
12 but not necessarily identical, to the training patterns.

13 One of the problems with conventional neural network
14 architectures as described above is that the training
15 methodology, generally known as the "back-propagation" method, is
16 often extremely slow in a number of important applications. In
17 addition, under the back-propagation method, the neural network
18 may result in erroneous results, which may require restarting of
19 training. Even after a neural network has been through a
20 training phase confidence that the best training has been
21 accomplished may sometimes be poor. If a new classification is
22 to be added to a trained neural network, the complete neural
23 network must be retrained. In addition, the weighting functions
24 generated during the training phase often cannot be interpreted
25 in ways that readily provide understanding of what they
26 particularly represent.

27

1 Thus, a neural network is typically considered to be a
2 trainable entity that can be taught to transform information for
3 a purpose. Neural networks are adaptable through a form of
4 training, which is usually by example. Long training times is a
5 problem in trainable neural networks.

6 The spatial image processor is part of a new neural network
7 technology that is constructed rather than trained as in common
8 neural networks. Since the words "neural network" often connote
9 a totally trainable neural network, the full definition of a
10 constructed neural network, as used herein, is as follows: A
11 constructed neural network is a connectionist neural network
12 system that is assembled using common neural network components
13 to perform a specific process. The assembly is analogous to the
14 construction of an electronic assembly using resistors,
15 transistors, integrated circuits and other simple electronic
16 parts. Some examples of common neural components are specific
17 values and/or types of connections, processing elements
18 (neurons), output functions, gain elements and other artificial
19 neural network parts. As in electronics, the laws of nature,
20 such as mathematics, physics, chemistry, mechanics, and "Rules of
21 Experience" govern the assembly and architecture of a constructed
22 neural network. A constructed neural network, which is assembled
23 for a specific process without the necessity of training, can be
24 considered equivalent to a trained common neural network with an
25 infinite training sequence that has attained an output error of
26 zero. Most neural network systems of many constructed neural
27 network modules, such as the spatial objects data fuser, have

1 weights that are never altered after they are constructed. When
2 the traditional neural network system is trained, learning occurs
3 only in special memory modules. Such special memory modules are
4 part of this new constructed neural network technology that
5 learns an example in a single application and does not require a
6 retraining of the old examples when a new example is added to a
7 previously trained system, i.e., old memory is retained and not
8 altered.

9 In artificial neural networks various neural components have
10 synonyms. For example a "neuron", a "processing element" and a
11 "processing node" are the same. A "connection value", a "weight
12 value" and "weighting value" are the same. One or more of such
13 synonyms are used in this and or other associated applications.

14 Despite advances in spatial image processors, there remains
15 a need for a spatial image processor neural network wherein the
16 spatial image processor neural network has a very high neuron
17 count (approximately 10^5 to 10^8 neurons), depending on the
18 multidimensional space the neural network modules operate, and is
19 of an architectural structure providing unique attributes:

- 20 (1) The spatial image processor discriminates between two groups
21 comprised of identical components in two different spatial
22 configurations. It is noted that most all image recognition
23 systems cannot discriminate between two such groups.
- 24 (2) The spatial image processor increases its sensitivity or
25 attention to an object of interest in a field of more than
26 one object.

- 1 (3) The spatial image processor increases its sensitivity to an
2 object of interest in a field where one or more other
3 objects are of non-interest.
- 4 (4) The spatial image processor recognizes a partially hidden
5 object when the object is incomplete or is bisected by one
6 or more other objects.
- 7 (5) The spatial image processor recognizes one or more objects
8 in a field of many different objects.
- 9 (6) The spatial image processor interfaces with an external
10 neural network or system (not described herein) that
11 uninhibits an object that becomes the spatial image
12 processor's "choice" of object to be fully recognized and to
13 be attentive of the object when such an object is in or
14 enters the visual field.
- 15 (7) The spatial image processor has a prototype output that
16 represents the general class of a recognized object
17 regardless of the status of the external system activations.
- 18 (8) The spatial image processor contains a low level of
19 processing outputs that represent peripheral vision
20 recognition outputs. Each of the processed outputs provides
21 an activation for a component object image in any position
22 on the retina.
- 23 (9) The spatial image processor recognizes various sizes of the
24 same object. An object, subtending varying size virtual
25 images in the image field, as it is viewed from near to far,
26 is continuously recognized as the same object.
- 27

- 1 (10) A first embodiment of a spatial image processor "retina"
2 contains a connection set that gives it a natural image
3 position invariant processing retina.
- 4 (11) A second embodiment of a spatial image processor "retina"
5 contains a connection set that gives it a natural processing
6 fovea. The foveating (foveal vision) retina contains a
7 "natural sweet spot of recognition" without an architecture
8 of geometric division to provide this process. It is noted
9 that the general definition of a foveating retina, or foveal
10 vision, has two defining human characteristics. One is that
11 an image seen in bright light is sensed in color as the
12 fovea contains mostly cones. The second is that the fovea
13 contains an area of the eye having a high concentration of
14 photonic elements to produce recognitions with fine detail
15 in contrast to the course detail of peripheral vision. The
16 spatial image processor uses a high resolution monochrome
17 photo transducer through out the retina.
- 18 (12) The spatial image processor senses a spatial arrangement of
19 component objects to process a temporal signal containing
20 the spatial data.
- 21 (13) The spatial image processor has a high memory efficiency as
22 it can use a component object in more than one high level
23 object of recognition.
- 24 (14) The spatial image processor uses linear neurons in most all
25 neural network processings.
- 26 (15) The spatial image processor architecture is designed and
27 operates under one or more technologies such as constructed

1 neural network, concurrent multiple frequency band and
2 synchronous nonlinear dynamical (chaos) technologies.

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SUMMARY OF THE INVENTION

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It is, then, an object of the invention to provide a spatial
image processor neural network having the desired attributes
noted herein immediately above.

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With the above and other objects in view, as will
hereinafter appear, a feature of the present invention is the
provision of a spatial image processor neural network for
processing image data to discriminate a first spatial
configuration of component objects from a second configuration of
identical component objects, the network comprising: a photo
transducer input array for converting a virtual image to pixel
data and sending a signal indicative of said pixel data; a
localized gain network (LGN) module for receiving the signal
indicative of the pixel data, wherein each input pixel drives a
corresponding neuron, and increasing the gain of individual
neurons as a function of attention activations; and a retina
array and parallel memory processor for receiving the pixel data
from the LGN module, for processing the pixel data into memory
vectors and for generating a signal including attention
activators for the localized gain network module and synchronous
temporal activations. The network further comprises neuron
arrays, component recognition vectors and chaotic oscillators
(nonlinear dynamical oscillators) assembly for receiving the
memory vectors, for receiving associative connection feedback and

1 for sending feedback data to the retina array and parallel memory
2 processor. Each of the component recognition vectors is operable
3 to activate a chaotic oscillator, with each of the chaotic
4 oscillators being different each to represent one of the
5 component objects. The component recognition vectors further
6 send peripheral vision object activations. The network also
7 includes a temporal spatial retina for receiving the pixel data
8 from the localized gain network module and the temporal
9 activations from the component recognition vector assembly and
10 parallel memory processor, for generating temporal spatial data
11 and for sending temporal spatial vectors. Also, a temporal
12 parallel memory processor receives the temporal spatial vectors
13 from the temporal spatial retina and sends temporal component
14 memory vectors. The network still further comprises a temporal,
15 spatial and object recognition vector array for receiving the
16 temporal component memory vector from the temporal retina array
17 and parallel memory processor and external associative
18 connections, for forming an object representation of the first
19 configuration of component objects, for sending prototype object
20 activations and for sending the associative connection feedback
21 to the neuron array, component recognition vectors, and to
22 synchronize chaotic oscillator assemblies, which in turn further
23 increases the attentive signal for feedback to the LGN and
24 temporal spatial retina.

25 The above and other features of the invention, including
26 various novel details of construction and combinations of parts,
27 will now be more particularly described with reference to the

1 accompanying drawings and pointed out in the claims. It will be
2 understood that the particular network arrangement embodying the
3 invention is shown by way of illustration only and not as a
4 limitation of the invention. The principles and features of this
5 invention may be employed in various and numerous embodiments
6 without departing from the scope of the invention.

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BRIEF DESCRIPTION OF THE DRAWINGS

9 A more complete understanding of the invention and many of
10 the attendant advantages thereto will be readily appreciated as
11 the same becomes better understood by reference to the following
12 detailed description when considered in conjunction with the
13 accompanying drawings wherein like reference numerals refer to
14 like parts and wherein:

15 FIG. 1 is a block diagram of one form of a spatial image
16 processor neural network illustrative of an embodiment of the
17 invention;

18 FIG. 2 is a side elevational view of a car comprising a
19 multiplicity of components;

20 FIG. 3 is a side elevational view, similar to FIG. 2, but
21 showing the identical car components in a different arrangement;

22 FIG. 4 is a side elevational view of the car of FIG. 2, but
23 in part obstructed from view;

24 FIG. 5 is an enlarged block diagram showing input array and
25 localized gain network portions of the network of FIG. 1, with a
26 portion thereof shown diagrammatically broken out and enlarged;

27

1 FIG. 6 is a block diagram illustrating internal portions and
2 functions of a parallel memory processor and neuron array of FIG.
3 1;

4 FIG. 7 is a diagrammatic illustration of a portion of the
5 localized gain network and parallel memory processor and neuron
6 array of FIG. 6;

7 FIG. 8 is a diagrammatic illustration of further portions
8 and functions of the parallel memory processor and neuron array
9 of FIGS. 1 and 6;

10 FIG. 9 is an enlarged diagrammatic view of components and
11 functions of a portion of the parallel memory processor and
12 neuron array of FIG. 8;

13 FIG. 10 is a diagrammatic representation of an arrangement
14 and functions of portions of component vectors and chaotic
15 oscillators assembly of FIG. 1;

16 FIGS. 11 and 11A are diagrammatic representations of an
17 arrangement and function of a chaotic oscillators portion of the
18 component recognition vectors assembly of FIG. 1;

19 FIG. 12 is a diagrammatic representation of functions of
20 portions of a temporal spatial retina of FIG. 1;

21 FIG. 13 is a diagrammatic representation of neuron
22 connection values in the temporal spatial retina of FIGS. 1 and
23 12;

24 FIG. 14 shows an exemplar image of ten pixels at two
25 different scales, or distances, including temporal pulses;

26

1 FIGS. 15-19 are diagrammatic representations of neuron
2 connection sets and temporal activations for the exemplar image
3 of FIG. 13;

4 FIG. 20 is a diagrammatic representation an additional
5 neuron connection set and temporal activation for the exemplar
6 image of FIG. 13, including an illustration of two connection
7 sets superimposed;

8 FIG. 21 is a combined graphical depiction of the temporal
9 spatial data activities of FIGS. 14-20;

10 FIG. 22 is a diagrammatic representation of an arrangement
11 and functions of portions of a temporal parallel memory processor
12 of FIG. 1;

13 FIG. 23 is a further diagrammatic representation of
14 functions of portions of the temporal parallel memory processor
15 of FIGS. 1 and 22;

16 FIG. 24 is an enlarged diagrammatic representation of a
17 portion of the temporal parallel memory processor of FIG. 23;

18 FIG. 25 is a detailed diagrammatic representation of a
19 portion of the network subassembly of FIG. 24;

20 FIG. 26 is a detailed diagrammatic representation of
21 portions of the temporal parallel memory processor and temporal
22 component vectors of FIG. 1;

23 FIG. 27 is a detailed diagrammatic representations of the
24 temporal component vectors and portions of a spatial recognition
25 vector array of FIG. 1; and

26 FIGS. 28-30 are diagrammatic representations of an alternate
27 embodiment of the spatial image processor and its components.

DESCRIPTION OF THE PREFERRED EMBODIMENT

Referring to FIG. 1, there is shown the overall architecture for the preferred embodiment of spatial image processor 10. It will be seen that a photo transducer input array 40 converts a virtual image 42 to an array of scaler data, which is called "pixel data" 44. The pixel data 44 initially passes through a localized gain network (LGN) module 45 without change, the unchanged output of LGN 45 referred to as pixel data 44a. Pixel data 44a is forwarded (referred to as pixel data 44b) to a parallel memory processor and neuron array 46, which processes the pixel data into component recognition vectors 49.

More specifically, the component recognition vectors 49 are the result of sparse neural activations that represent a specific virtual image on the input array 40. The appropriate component recognition vectors 49 activate all component objects that are recognized in a neuron array and component recognition vectors assembly 48. For each recognized object activation, a periodic broadband impulse 104 is fed back toward one or more relative pixel positions in the signal path that provided the gradient data for the component recognition vector 49. A feedback signal 50 goes to LGN module 45 and to a temporal spatial retina 52, referred to as 50a and 50b, respectively. In the LGN 45 module, the feedback signal 50a partially increases the neuron gain to increase the sensitivity, or attention, of spatial image processor 10 for each component object it recognizes. That is, the feedback signal 50 serves as attention activations 50a. The temporal spatial retina 52 also receives the same feedback

1 signal, referred to as temporal activations 50b. LGN 45 pixel
2 data 44a is also provided to temporal spatial retina 52, referred
3 to as pixel data 44c. The impulse signals merge with LGN 45
4 pixel data 44c in the temporal spatial retina 52 as temporal
5 component objects, each with unique identifying temporal
6 activations. Each temporal component activation occurs at a
7 different time to represent the position and identification of a
8 specific component object relative to other component objects.
9 The virtual spatial retina 52 merges the sequential temporal
10 activations 50b in their relative positions to each other to
11 generate sequences of pulses containing amplitude information
12 representing a spatial configuration of component objects making
13 up a super object 60, i.e., the object of interest in the scene.
14 This temporal spatial retina output data 54 is processed in a
15 temporal parallel memory processor 56 into temporal component
16 recognition vectors 122 in a similar manner as described for
17 processor 46. The component recognition vectors 122 in turn are
18 processed into component activations. Each component activation
19 contains information on its relative spatial configuration
20 relative to all components that make up the overall super object
21 60, and the activations are recognized in a spatial recognition
22 vector array 58. The overall super object 60 has associative
23 connections 172 to each of the component objects that it consists
24 of, which are fed into assembly 48 as associative connections
25 feedback 172. The associative connections feedback 172 are
26 processed within assembly 48 to enhance the broadband impulse
27 104. The activation of these connections by the recognition of

1 the overall super object increases the amplitude of the temporal
2 activations only for the associative component objects. The
3 feedback signal attention activation 50a in the LGN module 45
4 increases the attention gain to a higher level for the specific
5 component objects, thereby the overall object becomes an
6 attentive object representation 60.

7 The spatial image processor 10 can shift its attention under
8 external control through a set of external associative
9 connections 62. Consider the following three scenarios
10 reflecting external associative connections 62 where one of three
11 different active conditions, such as "tired of walking",
12 "hungry", or "thirsty" exist and the spatial image processor 10
13 is viewing the scene in FIG. 4. There are at least two, and
14 perhaps many, external associative connections 62 that can effect
15 the spatial image processor 10 relative to the specific input
16 scene. One is between the tired mode and the old car recognition
17 neural circuit (*as the car represents a possible ride*) and the
18 other is the hungry mode and the tree object recognition neural
19 circuit (*the tree is a possible source of fruits or nuts*).
20 Either recognition neural circuit is enabled by the tired or
21 hungry activation output to allow it to become fully attentive
22 through feedback. The tired mode causes the spatial image
23 processor 10 to attentively recognize the old car, as described
24 in the paragraph above. If the mode is shifted to hunger, the
25 feedback to the car component objects becomes inhibited and the
26 tree object components become enabled. In the thirsty mode,
27 there are no attention object representations 60 for objects in

1 the given image, as the scene contains nothing of interest.
2 Thus, there are no full attention activations. Under this mode,
3 all previous trained recognizable component objects have an
4 initial low-level attention activation. An initial low-level
5 attention allows the spatial image processor 10 to quickly change
6 its mode to full attention for objects it knows and to ignore
7 irrelevant visual information when enabled by the external
8 associative connections 62. Also, the spatial image processor 10
9 will still have prototype object activations 64 for all correct
10 spatially configured objects in the image data.

11 The spatial image processor 10 recognizes a partially hidden
12 object because the relative spatial configuration information is
13 encoded in each component that makes up the visualized object 60
14 and is recognized in the spatial recognition vector array 58. In
15 a divided or partially exposed object, all of the recognizable
16 and visible components maintain the correct spatial
17 configurations that will allow super object 60 recognition.

18 Referring to FIGS. 1 and 5, it will be seen that the spatial
19 image processor 10 receives image data into the photo transducer
20 input array 40 to become pixel data. Input array 40 converts
21 image data to scalar values of pixel datum relative to the image
22 intensities. The pixel array has the dimensions of P by Q, or
23 "s" pixel count. The scalar values of pixel data are connected
24 to the localized gain network (LGN) 45 of the same spatial
25 dimensions. The LGN 45 is named after the biological neural
26 group called the lateral geniculate nucleus of the thalamus that
27 modulates the optical pathway between the eye and the visual

1 cortex. LGN 45 and the biological system are both associated
2 with attention. The localized gain module 45a of LGN 45
3 increases the gain of individual neurons as a function of
4 attention activations 50a. The minimum neuron gain is one and it
5 increases its gain with the average energy of attention
6 activations 50a. Each input pixel has a corresponding neuron 68
7 within localized gain module-45a (FIG. 5). The spatial
8 relationship of the pixel array is preserved through LGN 45 and
9 in many of the modules in this invention, which is very important
10 to its processing ability. The output stage of LGN 45 is a
11 neural module called a vector normalizer 70 (FIG. 5). The vector
12 normalizer 70 adjusts the array of scalar data 44d from localized
13 gain module 45a into a normalized vector, or unit vector 44a of
14 the image pixel data via normalization activation 68a to neuron
15 68b. Each neuron 68 has a corresponding neuron 68b within
16 normalizer 70 as shown by circuit 75.

17 The array of scalars 44d is the output of all localized gain
18 module linear neurons 68, thus array 44d has a spatial dimension
19 equal to the photo transducer input array 40, as each neuron 68
20 corresponds to one of the "s" pixels. Thus, there are "s" neural
21 circuits 75 in LGN 45. This neural architecture, wherein each
22 pixel corresponds to a neural circuit, is represented throughout
23 the neural circuits of the spatial image processor 10, as will be
24 discussed further herein. The architecture allows an image in
25 any position on a retina to generate a signal flow from a spatial
26 $P \times Q$ organization to one or more image components in their fixed
27 neural positions in the spatial image processor 10 architecture

1 and then allows a feedback signal to return back to the same
2 retinal position in the temporal spatial retina 52.

3 Therefore, when the attention activations 50a occur, they
4 cause the contrast of the non-attentive pixel data to decrease
5 relative to the enhanced attentive pixel data. The vector of LGN
6 45 is processed by both the parallel memory processor 46, where
7 it is referred to as vector 44b, and by temporal parallel memory
8 processor 56, where it is referred to as vector 44c.

9 The four modules, i.e., the parallel memory processor and
10 neuron array 46, the component recognition vectors assembly 48,
11 the temporal parallel memory processor 56, and the spatial
12 recognition vector array 58, are described in U.S. Patent No.
13 5,446,828, incorporated herein by reference, and U.S. Patent
14 Application Serial No. 09/641,395. However, each of the modules
15 as described therein is modified by the removal and/or addition
16 of other constructed neural network parts, modules and feedback
17 paths added to the architecture to obtain the architecture of the
18 spatial image processor herein.

19 Referring now also to FIGS. 6 and 10, the parallel memory
20 processor and neuron array 46 is described in more detail.
21 Processor 46 processes the pixel data 44b into feature vectors
22 47. Feature vectors 47 contain "arbitrary features" such as the
23 development of unique signals caused by a deterministic
24 interaction between the spatial image processor 10 neural network
25 architecture and an input of an image that produces one or more
26 feature vectors 47 of an image. Each feature vector 47 is
27 relative to the image's local intensity gradients about a pixel

1 in a retina array. Feature vectors 47, which are developed from
2 similar intensity gradients, are grouped as "common features" 55.
3 Component recognition vectors 49 are the result of a process in
4 a space called the memory vector space 59. The sparse neural
5 activations within memory vector space 59 form memory vectors 63,
6 as shown in FIG. 10. Memory vector space 59 and a memory vector
7 63 have a corollary to the visual cortex in a brain and the
8 neural activity as seen in a position emission tomography and/or
9 a nuclear magnetic resonance process when a subject views an
10 object. The memory vector 63 is the equivalent of the pattern of
11 activity, caused by a stimulus, and the memory vector space 59 is
12 the equivalent of the "space" of the cerebral cortex where all
13 possible "recognition activities" may occur. Thus, when an input
14 stimulus is applied to the spatial image processor 10, a sparse
15 memory vector is active in the memory vector space.

16 The array of scalar data 44b from LGN 45 spatially
17 represents a retina of data. Therefore, LGN 45 output data 44b
18 "becomes" the spatially virtual retina 72, which is part of an
19 image position and size invariant retina 74 in parallel memory
20 processor 46. This assignment of the data 44b as the virtual
21 retina 72 provides a continuity and integration of U.S. Patent
22 Application Serial No. 09.641,395 into the spatial image
23 processor 10. The image position and size invariant retina 74
24 outputs a multidimensional feature vector 47 for each pixel in
25 the retina. The multidimensional feature vector 47 represents
26 the local image gradients about each pixel. Referring also to
27 FIGS. 7-9, a gradient window 78 is of a star sapphire-like shape

1 with many points that are lines of pixels. The central pixel in
2 the gradient window 78 is the reference pixel from which the
3 differences to all other pixels are formed in a window difference
4 neural network (WDN) 80. These differences are decoupled and
5 dispersed in a vector decoupler (VD) 82 and neural director (ND)
6 84 to produce the feature vectors 47. There is one feature
7 vector 47 for each pixel; thus, the image position and size
8 invariant retina 74 output feature vector 47 is a vector of local
9 vectors. There is a "dimensional explosion" of data as compared
10 to the image pixel data 44a to that of the image position and
11 size invariant retina 74 output 47. This dimensional increase
12 allows linear separation and collection of feature data in a
13 higher dimensional space.

14 The array of feature vectors 47 has a dimension of "s" times
15 "r", where "s" is the pixel dimension and "r" is the output
16 dimension of each ND 84, as shown in FIG. 7. The output
17 dimension "r" is proportional to the combinations of pixel
18 comparisons within gradient window 78.

19 The image position and size invariant retina 74 provides
20 output feature vectors 47 which are processed by a parallel set
21 of constructed neural network memory processors, each comprising
22 a multiplicity of multi-layer ND's 84, feedback and threshold
23 positional king of mountain networks (FTPKOM) 86, and sum neural
24 networks (SUM) 88. Each memory processor, with its multi-layer
25 ND's 84 and FTPKOM's 86, is a local processor that increases the
26 resolution of the local gradient data about a single reference
27 pixel (p,q) in the retina and then reduces it to a low

1 dimensional vector. Each of the local pixel (p,q) memory
2 processors operates independently on its local feature vector 47
3 up to the FTPKOM module output space. The local memory processor
4 functions similarly to that described in U.S. Patent Application
5 Serial Number 09/477,638. A FTPKOM module 86 (FIG. 9) is a
6 special positional king of the mountain (PKOM) device with
7 variations in its design. The first variation is the use of a
8 fixed or a dynamic threshold 92 that has its maximum level set to
9 a relative value of the highest peak neural director output for
10 all pixel (p,q) memory processors and for all neural director 84
11 layers. The minimum threshold is set relative to the peak self
12 noise, or image noise level of any pixel (p,q) memory processor
13 neural director 84 layer. This FTPKOM module 86, besides
14 limiting the output to one output, limits nonessential low
15 contrast image activations and inhibits any output when there is
16 not a graded pixel set around the associated reference pixel in
17 the image position and size invariant retina 74 (FIG. 6). At
18 least one or more neural director 84 output neurons must be
19 greater than the threshold 92 value to activate a FTPKOM module
20 86. The threshold operation will be covered in more detail
21 herein below. The second variation to the FTPKOM design is
22 associated with the feedback paths, to be discussed in the
23 paragraph below.

24 Continuing with the local memory processors, the FTPKOM
25 module 86 outputs 94, as shown in FIG. 8, are organized through
26 virtual common features 55. Each SUM 88 accumulates only similar
27 feature activations from each FTPKOM module 86 and each sum 88

1 neuron input value is subtracted by a threshold 88a value to
2 allow only essential features to the sum output neuron 88. Sum
3 neural network outputs 98 (FIGS. 6 and 8) become inputs to the
4 memory vector space 59.

5 Referring again to FIG. 10, a component recognition vector
6 49 is a matched filter instantly trained to recognize a whole
7 object, such as a component object or a temporal component
8 object. A component recognition vector 49 contains a neuron 67
9 (feedforward neuron) and a set of connections 79 matched to a
10 pattern called a memory vector 63, which is the result of an
11 input component object image. Each component recognition vector
12 49 is used to recognize a specific memory vector 63 of
13 activations.

14 An array of component recognition vector neurons 67 includes
15 feedforward neurons 67a, which activate the passage of a temporal
16 signal through a feedback neuron 67b. A combination of a
17 recognition vector neuron 67 and a group of component recognition
18 vector connections 79 provides for the output of the component
19 recognition vector 49. An active memory element 110 is shown in
20 FIG. 10 as a single active element to simplify the drawing and
21 the conception of the memory vector 63. Each active memory
22 element 110 is in reality the highest representation of a group
23 of individual activities of SUM's 88 (FIGS. 6 and 8). The
24 connection values for all sum neural networks are unit values and
25 comprise connection pairs 102 (FIG. 9). The connection pairs 102
26 conduct feature information in a feed forward mode and receive
27 feedback activations 104 in return along a parallel path. The

1 matching of sparse connections 79 of component recognition
2 vectors 49 to their memory vectors 63 is shown in FIG. 10, the
3 connections being learned in pairs of parallel paths. Each
4 connection pair 79 consists of a normalized vector element value
5 in the feedforward path and a unit connection value in the
6 feedback path.

7 Referring now also to FIG. 11, the activation of a component
8 recognition vector 49 produces a peripheral vision object
9 activation 66 (FIGS. 1 and 11) and activates its chaotic
10 oscillator 65 in component recognition vectors assembly 48 (FIG.
11 11). The architecture that allows two or more concurrent object
12 recognitions is the sparse connections 79 of the component
13 recognition vectors 49 (FIG. 10) and their component object
14 memory vectors 63 (FIG. 10) in a high dimensional space. The
15 component recognition vectors 49 provide spatial nonlinearities
16 in the memory vector space 59 of the component memory vectors 63
17 (FIG. 10), as well as the classic nonlinearities caused by
18 thresholds and/or FTPKOM circuits. The component recognition
19 vector processings and the virtual common feature space
20 architectures are the data paths that allow the peripheral
21 recognition of an object in any position of the retina. Also,
22 the storage and recognition efficiencies of this invention are
23 based upon the fact that low level component objects are stored
24 in memory, which can be used for other visual objects in
25 different spatial configurations. There are as many component
26 recognition vectors 49 as needed to support all of the output
27 classes in the preferred embodiment of the invention. At this

1 point in the architecture, the car components in FIGS. 2 and 3
2 will activate identical component objects.

3 The spatial image processor 10 provides peripheral vision
4 object activations 66 (FIG. 1) from low level component object
5 recognition activations 110 from a module of recognition vectors
6 49 (FIG. 11) of the parallel memory processor and neuron array 46
7 (FIG. 1) as a component object's optical image can be recognized
8 away from the retina's fovea center. In this instance, the term
9 "module" represents a neural circuit, a neural network or a
10 module of modules that performs a specific process. Modules 46,
11 48 and 56, 58 (that is, parallel memory processor and neuron
12 array 46, component recognition vectors assembly 48, temporal
13 parallel memory processor 56, and spatial recognition vector
14 array 58) are similar modules with similar processes and
15 components but with slight differences in each. Modules 46 and
16 56 receive the same pixel data signal through parallel paths, 44b
17 and 44c. Therefore, the active pathways to the component
18 recognition vectors are the same in each group of modules. The
19 modules 46, 48 connect the pixel data through a neural process to
20 specific component object recognitions and activate their chaotic
21 oscillators 65 which produce temporal output pulses. These
22 pulses (feedback) are only allowed travel along the same paths
23 (connection pairs carry feedforward signals and feedback
24 signals). The signal from the feedforward enables the feedback
25 at each neuron in the feedforward pathway. Thus, only the
26 temporal signal of one chaotic oscillator can follow the path
27 back toward the relative pixel positions that enabled it. This

1 feedback signal performs two processes. One is to increase the
2 gain of the image input path that activated itself (attention 50a
3 to the LGN) and the second is to apply the temporal signal 50b to
4 its relative pixel positions in the temporal spatial retina 52.
5 The "temporal" group of modules 56, 58 carry the pixel data
6 through the same pathways as the feedforward paths above, but in
7 the "temporal" group, these pixel signals activate each neuron's
8 ability to pass "common mode" or superposed temporal signals
9 through the feedforward process to its temporal component object
10 recognition vectors 122, comparable to the component object
11 recognition vectors 49 of module 46. Thus, only the temporal
12 pulses that started their path from the activation of chaotic
13 oscillators 65 find their way through spatial retina 52 and
14 processor 56 to temporal component object recognition vectors
15 122. The temporal signal is a broadband signal superposed on the
16 pixel data signal just as a video tape recorder "carries" the
17 bias signal on the video signal. The lower band pixel data (LGN
18 signal 44c) enables a neuron, in the feedforward path receiving
19 the pixel data, to also pass the broadband signal along the same
20 path. A broadband signal superposed on a negative or zero pixel
21 value signal cannot pass through a neuron in the temporal group
22 neural network. Thus, the temporal group operates as a
23 "specially controlled multiplexer circuit" to pass the temporal
24 pulses only to specific places in the neural circuit. The
25 special controlling signal is the input image itself and the
26 "multiplexed paths" are relatively continuous (not uniformly
27 stepped from sample to sample, except as changes of input images,

1 which change the temporal pulses from path to path). Note, since
2 both groups contain effectively the same modules the word
3 "temporal" precedes a neural network module name in the temporal
4 group; such as the "temporal component object recognition
5 vectors" 122, as opposed to the "component object recognition
6 vectors" 49.

7 A component object activation starts a narrow band chaotic
8 oscillator 65 (FIGS. 11 and 11A), of the type disclosed in U.S.
9 Patent No. 5,446,828, and modified to produce a series of
10 deterministic patterns. Each chaotic oscillator 65 produces a
11 different set of temporal patterns and contains a matched filter
12 96. The matched filter 96 and a dynamic threshold produces one
13 best match of the temporal patterns to produce a single broadband
14 output pulse per cycle of sequential patterns. The chaotic
15 oscillators 65 have similar repeatable pattern periods. The
16 matched output 104 of connection pairs 102 is a positive temporal
17 activation pulse that represents its component object at a
18 relative time and this pulse is fed back along each feedback
19 activation path of the connection pairs 102 (FIG. 9). The
20 relative time is in comparison to other associated common
21 component temporal pulses. The temporal activation 104 returns
22 through the feedback path of the component recognition vector 49
23 (FIG. 10) to a sum feedback neuron 106 (FIG. 8) and continues
24 back to each FTPKOM 86 that originally provided part of the
25 component recognition vector activation. While sum feedback
26 neuron 106 contains connection pairs 102, which feedback temporal
27 activations to all FTPKOM 86 circuits, the temporal activations

1 dead end at those FTPKOM 86 circuits that did not provide the
2 original feature activations for the component recognition vector
3 49 because the FTPKOM feedback neuron 108 (FIG. 9) is not enabled
4 for the specific feature. The active FTPKOM feedback neuron 108
5 that is enabled, as indicated by enabling path 94a of output 94,
6 feeds the temporal activations 104 through the FTPKOM sum neuron
7 186. At sum neuron 186, all activations 104 from enabled
8 feedback neurons 108 are combined together with temporal
9 activations from other neural director layers, designated as 50c
10 in FIGS. 8 and 9, to feedback signal 50. Thus, the temporal
11 activations 104, as 50c, pass through all FTPKOM layers to become
12 feedback signal 50, which is provided, as temporal activations
13 50b, to the relative neuron positions in the temporal spatial
14 retina 52 represented by the FTPKOM. The temporal activations 50
15 are also passed to the same relative neuron position (as 50a) in
16 the LGN module 45, where the energy in the temporal activations
17 50a increases the gain of the specific LGN neuron 68. These
18 local gain changes increase the attention of the component object
19 by sharpening the virtual image gradients, or image contrast,
20 about the component object and reducing the gradients for all
21 other objects not activated. The vector normalizer 70 (FIG. 5)
22 causes a reduction of other gradients when the attention gain is
23 increased. The processing function of a vector normalizer 70, in
24 LGN 45, is to generate and maintain a unit vector from all pixel
25 element values. Thus, when a selected group of pixel neurons 68
26 of an object attention are increased in gain, the greater
27 attentive pixel element values will reduce the contrast of all

1 other non-essential images. High attentive values have the
2 ability to effectively "remove" other images from the field of
3 image processing.

4 Referring now to FIG. 12, the temporal spatial retina 52
5 (FIGS. 1 and 12) contains an architecture that senses the spatial
6 configurations of the component objects. The temporal spatial
7 retina 52, as shown in FIG. 12, contains two arrays 112, 114 of
8 neurons. The input array is the temporal retina 112 and the
9 output array is the spatial retina 114 that combines temporal
10 signals with each LGN pixel datum 44c into temporal spatial data
11 signals 54. Each retina of temporal spatial retina 52 contains
12 an array of neurons in the same pixel orientation as the input
13 array 40 or each of the arrays of the LGN 45 neurons 68, 68b
14 (FIG. 5). In FIG. 12, each spatial retina neuron 118 is
15 connected, respectively, from the appropriate LGN neuron 68b and
16 the appropriate temporal activation connections from temporal
17 retina array 112. Various component object temporal signals from
18 50b activate temporal retina neurons 116 and are distributed,
19 through connections, to the spatial retina neurons 118 to
20 generate the multiple temporal signals. The temporal signals are
21 further superposed into the relatively steady LGN output pixel
22 data 44c. The temporal and LGN signals are processed in
23 different ways. Both activations, from 44c and 50b, become two-
24 dimensional signal 54. Thus signal 54 can be seen to have two
25 components: 54b, the slower changing LGN output signal (low
26 bandwidth) from 44c; and 54a, the broadband signal from 50b,
27 superposed on 54b. It then activates the multidimensional

1 gradient data through their active paths in temporal parallel
2 memory processor 56 and spatial recognition vector array 58.
3 Signal 54b is processed through processor 56 in the same manner
4 as pixel signal 44b is processed through processor 46. The
5 positive values of the signal 54b are used in processor 56 to
6 control the active paths of the broadband temporal signals 54a.
7 Each neuron in processor 56 and array 58 that operates upon
8 signal 54b contains a broadband neuron component that is
9 positively activated only when signal 54b has an activation
10 corresponding to that neuron. These activations are the way that
11 the multipath signals 54a are passed through the temporal neural
12 modules.

13 A Dynamic Temporal Input Enable (DTIE) 114a module receives
14 all 44c signals and generates an output value that is a
15 proportion of the peak pixel signal 44c and enables selective
16 temporal signals 50b received by the spatial retina 114. All
17 spatial retina neurons 118 receive an enable signal 115 from DTIE
18 114a that will enable a neuron 118 to accept temporal signals
19 from the temporal retina 112 providing the neuron 118 has a 44c
20 pixel input value greater than the enable signal 115. The enable
21 signal 115 does not affect the values of pixel signals 44c to any
22 neuron 118, nor does it change the input values from the temporal
23 retina 112 for the neuron 118 that is enabled. All neurons 118
24 not enabled do not receive temporal signals from temporal retina
25 112.

26 Each neuron 116 in array 112 of temporal spatial retina 52
27 is fully connected to a neuron 118 in the array 114. Each

1 connection weighting values are calculated as shown in FIG. 13,
2 for example, where array 112 is shown superposed on array 114
3 (dashed lines). Retina neurons 116 on the input array 112 are
4 labeled as P' and output neurons 118 are labeled as P . $P(a)$ is
5 an arbitrary output neuron 118 connected to arbitrary exemplar
6 input neurons 116 such as $P'(b)$, $P'(c)$ through $P'(j)$. The
7 Euclidean planar distances between pairs of the superposed
8 neurons are identified as "b" through "j". The connection weight
9 values between the arrays 112, 114 from the input neurons ($P'(s)$,
10 116) and the output neuron ($P(s)$, 118) are functions of the
11 spatial positions of each pair of neurons. The weight value for
12 the connection between $P'(b)$ and $P(a)$ is the ratio of kb/E_R ,
13 where E_R is the maximum Euclidean distance across the retina; b
14 is the Euclidean distance between neurons $P'(b)$, 116 and $P(a)$,
15 118; and k is a constant. The weight between $P'(c)$ and $P(a)$ is
16 kc/E_R , and so forth. The retina 52 design of connection
17 configurations for each neuron 118 from all neurons 116, is a set
18 of connections that generate a gradient of "iso-connection value
19 radii". The temporal connection value between spatially
20 identical superposed neurons $P(s)$ and $P'(s)$ is zero, as neurons
21 116, 118 are spatially superposed, making the Euclidean distance
22 value zero. (Note that a distance value of zero equates to no
23 connectivity of data). To generate all temporal connections from
24 neuron 116 of temporal retina 112 to neurons 118 of spatial
25 retina 114, choose a neuron 116 and determine the Euclidian
26 distances between the neuron 116 and each neuron 118 and

1 calculate each connection value as ks/E_r , where s is the
2 Euclidian distance between the neuron 116 and the respective
3 neurons 118. Select a second neuron 116 and repeat the above
4 process until all neurons 116 are connected to all neurons 118.
5 Connection values activated by an image, in a fixed spatial size,
6 will produce identical connection weight values regardless of the
7 translational or rotational position of said image on retina 52.

8 Examples of proportional valued connections and their
9 temporal spatial data are shown in FIGS. 13 and 15-21. FIG. 13
10 shows an example of connections generated where one neuron 118,
11 $P(a)$, is connected to nine neurons 116, $P'(b)$ through $P'(j)$.
12 Temporal activations that represent component object temporal
13 pulses 50b at temporal retina 112, one each at the input neurons
14 116, $P'(b)$, through $P'(j)$, are shown in FIG. 14 for each
15 connection as shown in FIGS. 13 and 15. The ten active pixels
16 (neurons 116 with signal 50b and/or neurons 118 with signal 44c)
17 of the exemplar image of FIG. 14 are used to generate spatial
18 configuration data as component object processes for the temporal
19 spatial retina 53, for the temporal parallel memory processor 56
20 and for the spatial recognition array 58. The temporal
21 activations 50b cover the feature areas of each component object,
22 but only a single representative neuron for each component object
23 is shown in the example. The connection sets in FIGS. 15-20 have
24 temporal spatial activities 54a from each output neuron 118 at
25 $P(a)$, connection set b at $P(b)$, and so forth. Assume that all
26 component chaotic oscillators 65 are synchronized in their
27 periods, but not in their activations, and each oscillator

1 generates a single temporal pulse activation within each
2 repeating period. Therefore, the temporal pulse activations 50b
3 in retina 112 occur at different times and will repeat over time,
4 as shown in FIGS. 14. The physical spatial configuration of
5 component object temporal pulse activations 50b at neurons 116 of
6 retina 112 are interconnected through the unique architecture of
7 the connections to neuron 118 of retina 114 to develop sets of
8 temporal spatial data activations 54a at each corresponding
9 neuron 118 and also to generate pulse amplitudes that contain
10 information on the relative component object spatial
11 configurations. Each set of temporal spatial data activations
12 54a and their Euclidian connection configurations for each neuron
13 118, P(a) through P(j), are shown in FIGS. 15-20. Each set of
14 temporal spatial data activations 54a represents a repeating
15 vector, where each amplitude at time "t" is an element of the
16 vector. A partial set of possible activations 54a are shown in
17 their exemplar timing order t(b), t(j), t(h), t(i), t(a), t(f),
18 t(g), t(c), t(e) and t(d). Each output neuron 118 will see nine
19 sets of activations in the above order per each temporal period
20 of time, with a different set of temporal activation amplitudes
21 dependent upon the spatial configuration of each component object
22 and their connection value between said component object image on
23 retina 52. The ten segments of temporal spatial data amplitudes
24 for each of the connection sets each represent the actual spatial
25 configuration of the ten component objects in a "multiple
26 triangulation lock", as illustrated by the two component object
27 triangular lock for connection sets i and j in FIG 20. That is,

1 each component has two or more other components in spatial
2 triangles, which remain in constant ratios over image translation
3 and/or scale size changes. Additionally, the ratios are
4 sensitive to, and can discriminate component object changes in,
5 alternate spatial configurations. It becomes obvious, using
6 connection sets i and j as shown in FIG. 20, that the Euclidian
7 geometry of the connection sets for the two output neurons, $P(b)$
8 and $P(i)$, contains the "multiple triangular locks", which produce
9 two representable sets of temporal spatial data activations 54a.

10 Thus, an input image containing hidden and/or divided component
11 objects of a super object 60 may still result in a large number
12 of "multiple triangular locks" so as to reliably provide a
13 recognition of said super object 60 even when some triangular
14 locks are missing. A super object 60 with a high multiplicity of
15 triangular locks will also provide a high sensitivity to
16 alterations in the component object spatial configurations and/or
17 a high sensitive discrimination between similar images. In FIGS.
18 15-20, the multidimensional information in each component object
19 output neuron 118 generates a temporal vector that is used for
20 and contains the spatial configuration for recognition of a super
21 object 60 image. Images containing a sufficient number of
22 component objects can be recognized when an image is partially
23 hidden or divided as the likelihood of the remaining visible
24 configured component objects remain high, thus providing
25 recognition. Humans do this mental process once they have
26 learned an object by assuming the hidden components are still
27 part of the whole object. The multiple neurons 118 outputs 54a

1 will reinforce the recognition process of a spatial component
2 object configuration. The multiple outputs, which represent
3 component object images encompassing an area greater than a
4 single pixel, are not shown.

5 FIG. 14 also illustrates a distant input image, Image',
6 which represents the same component objects and configuration as
7 in connection set a, but at a different scale size of virtual
8 image, i.e., further away from the retina. The temporal data for
9 the connection set a' is shown in FIG. 15. The set a' connection
10 values have identical ratios to those of connection set a, and
11 will generate proportional temporal spatial data 54a, where each
12 repeating vector from set a and a' point in identical directions
13 in a multi-dimensional space. However, they contain vector
14 magnitude differences representing different image sizes.

15 FIGS. 15-20 each show series of pulses, or pulse trains
16 converted into pulses of temporal spatial data 54a for their
17 respective connection sets, where each pulse has a different
18 amplitude. FIG. 21 groups these pulse trains into a single
19 figure for ease of comparison. The temporal spatial data repeats
20 in time and is shown only for three cycles. One cycle in each
21 temporal spatial data activation 54a is identified and the pulse
22 amplitudes for the ten time marks are each different in each
23 temporal spatial data activation 54a, except for reciprocal
24 connection values. Note that one of the time marks in each group
25 has an amplitude of zero due to its connection value of zero.
26 Also, all temporal spatial data activations 54a, representing one
27 super object 60, are in synchrony with each other, as each pulse

1 active at one instant of time is the same component object
2 activation 50b of FIG. 14. FIGS. 13 and 15-20 identify component
3 object spatial configurations in a superposition of retinas 112
4 and 114 and show only the relevant connections in each connection
5 set that develop the respective temporal spatial data 54a signal
6 trains of FIG. 21. The relative amplitudes contain the spatial
7 relationship between the ten input neurons 116/118, where each
8 connection set is a different relational aspect of the ten
9 neurons, and show each temporal spatial data generated by their
10 respective neural connection aspects. Identical input images
11 shown in FIG. 14, each activates its appropriate connection set a
12 or set a' as shown in FIG. 15, and each input image has the same
13 input aspect and image spatial configurations, although of
14 different sizes. Thus, the temporal spatial retina 52 generates
15 identical amplitude ratios within each temporal spatial data
16 activations 54a, providing identical temporal vector directions
17 that represent identical recognitions. The spatial image
18 processor 10 processes multidimensional vectors and temporal
19 multidimensional vectors to determine the vectors' directions in
20 a multidimensional space as a recognition process.

21 Referring now also to FIGS. -22-27, the steady state LGN data
22 44c passes through the temporal spatial retina 52 unchanged and
23 becomes the signal 54b component of signal 54 input to temporal
24 parallel memory processor 56. The LGN data 54b is processed in
25 the temporal parallel memory processor 56 exactly as the pixel
26 data is processed in the parallel memory processor and neuron
27 array 46 (FIGS. 1 and 6). Besides the existence of the feedback

1 paths in processor 46, the LGN data 54b in FIG. 22 produces the
2 same temporal component memory vectors 122 as the component
3 memory vectors 49 shown in FIG. 6. The TPKOM 124 of FIG. 24 are
4 the same as the FTPKOM 86, but they do not contain feedback
5 circuits. The TPKOM 124, besides limiting the output to a single
6 output connection 128, in conjunction with the dynamic threshold
7 130, also limits the nonessential low energy activations and
8 inhibits an output when there is not a sufficient gradient in the
9 gradient window of retina array 72a. The TPKOM circuit is
10 controlled by a dynamic threshold 130, as discussed above, and as
11 shown in FIGS. 23 and 24. The dynamic threshold 130 receives the
12 output energy 132 (FIG. 24) from all neural director 134 output
13 neurons (FIG. 23) in its layer, shown as 132a in FIG. 24.
14 Threshold 130 then develops a threshold as a percentage of the
15 highest energy (as required by design considerations) and passes
16 the threshold, as 132b, to all PKOM modules 126 (FIGS. 24 and 25)
17 in the same layer. The threshold is subtracted from each input
18 neuron 136, as seen in FIG. 25. The output neuron 134 has a "t"
19 and INH inputs. Any INH positive value input will
20 unconditionally inhibit the output neuron 134. The "t" input,
21 when a positive value, will allow an output of a unit value,
22 otherwise the output is zero. The input neuron 136 that contains
23 the highest positive output value will produce all negative
24 outputs in its own difference layer allowing a unit output to
25 occur through its "t" connection. The highest output of an input
26 neuron 136 will inhibit all other output neurons 134. When the
27 threshold is the highest of all inputs, then all of the output

1 neurons 134 are zero. It is noted that the threshold 92
2 operation for FTPKOM 86 (FIG. 9) operates in the same manner as
3 threshold 130 of TPKOM 124, i.e., threshold 92 receives the
4 output energy 132c (FIG. 9) from all neural director 84 output
5 neurons (FIG. 8) in its layer. Further, the operation of FTPKOM
6 86 is the same as that described for TPKOM 124 relative to FIG.
7 25, with the exception of the "t" connection in TPKOM 124 and the
8 feedback in FTPKOM 86. Furthermore, the operation of the sum
9 circuit 88 is the same as that of sum circuit 89, with the
10 exception of the temporal activations 54a described below.

11 The temporal activations 54a, being a superposed signal,
12 require minor additions that do not alter the LGN data 54b paths
13 from the spatial retina array 114 through a temporal component
14 object recognition vector 122. The LGN output signal 54b and the
15 temporal activations 54a are mostly separated in the frequency
16 domain in a manner similar to the video, or audio, being
17 separated from its bias signal in a magnetic tape recorder. The
18 broadband narrow pulses of the temporal spatial data activations
19 54a contain frequencies in a higher band than the LGN signal 54b
20 from the image data. Each neuron in the LGN signal 54b path,
21 from the spatial retina 114 in FIG. 12 through to the sum neuron
22 89 in FIG. 23, processes signals two ways. The LGN signal 54b is
23 processed in a feedforward normal neural network method through
24 to temporal recognition vectors 122 (FIG. 26). The same LGN
25 signal 54b activation at each feedforward neuron also enables the
26 passing of the temporal spatial data signal 54a, only for
27 positive signals above a threshold, if one exists. All other LGN

1 signals 54b will inhibit any temporal signals from passing
2 through the output of any of the neurons in the temporal neural
3 networks. The neurons 144 of the temporal component object
4 recognition vectors 122 operate the same as the other temporal
5 neurons except they do not pass any of the LGN signals 54b. They
6 pass only the temporal broadband signals 54a to a spatial
7 recognition vector array 58 (FIG. 27), when enabled by the LGN
8 signals 54b. Every temporal neuron passes the temporal signal
9 54a in proportion to the level of the positive LGN signal 54b at
10 the output of the temporal neuron. That is, the appropriate
11 positive LGN signal 54b controls the gain of the temporal signal
12 passed through the neuron.

13 The temporal activations 54a use a wide band circuit that
14 enhances only the common mode or superposed signal in the path of
15 active LGN signals 54b. Each neuron in temporal parallel memory
16 processor 56 contains a simple, positive signal, gain controlled,
17 broadband coupled circuit. "Each neuron", as used herein, refers
18 to all neurons from the spatial retina 114 output 54 (FIG. 12)
19 through temporal component recognition vector 122 (FIG. 26), with
20 an exception as noted above. The steady state positive value of
21 each neuron 144 (FIG. 26) proportionally controls the coupling of
22 its temporally activated common mode signal 54a through the
23 neuron 144. Zero or negative output signals do not allow the
24 passage of the common mode signal. This neuron configuration
25 allows the common mode signal 54a to follow the activations of
26 the component features through the neural network to the temporal
27 component memory vector space 140 (FIG. 22).

1 The LGN pixel data 54b carries the temporal activations 54a
2 through to active memory elements 110a of temporal memory space
3 140, memory vectors 51 and connections 77, as shown in FIG. 26
4 (corresponding to elements 110, vectors 63 and connections 79 of
5 FIG. 10). The output neurons 144 activate the broadband coupled
6 circuit that allows only the temporal activations 54a to pass to
7 its output. The low band temporal signal 54b of activations 51
8 and connections 77 do not couple through to the output of this
9 neuron type. Broadband activations 54a from an array of temporal
10 component recognition vector output neurons 144 (FIGS. 26, 27)
11 become the temporal component recognition vector 122 input to
12 spatial recognition vector array 58. Spatial recognition vector
13 array 58 may represent a class example of cars and the
14 recognition of a super object may represent a specific type of
15 object from that class such as an old car, 57 Chevy, or a VW Bug,
16 each having a unique spatial orientation of their component
17 objects as provided in peripheral vision object activations 66.
18 Each super object class is processed in a spatial recognition
19 vector array 58. Inputs 122 to spatial recognition vector array
20 58 are received at spatial recognition delay vector array (DVA)
21 146. DVA 146 is an array of delay vectors 288 of which each
22 delay element 148 contains a single "learning" delay element and
23 each delay vector 288 is connected to a Threshold and Hold Multi-
24 King Of the Mountain (THMKOM) 150 and to a prototype
25 "classification" neuron 156. The positive sensing Multi-King Of
26 the Mountain (MKOM) circuit is one of two (positive and negative)
27 MKOM circuits fully described in relation to U.S. Patent

1 Application Serial No. 09/477,653. Each delay vector 288
2 contains specific delay values that relatively alter a group of
3 time elements from a spike train, as shown in the examples of
4 FIG. 21, into a momentary vector of scalar elements. The scalar
5 elements are processed as any set of scalar vector elements in a
6 constructed neural network. The delay vector 288 aligns a period
7 of temporal amplitude activations from signal 54a into a
8 momentary multidimensional vector in which the vectors spatial
9 direction is used for recognition of a super object.

10 A threshold and hold (TH) module 280 provides two processes
11 to the connected THMKOM 150 array. In one process, the THMKOM
12 150 generates a threshold to the momentary input vector. The
13 other process is a sample and hold process in synchrony with the
14 output of neuron 156 to maintain the momentary vector values for
15 a longer time but less than one period of signal 54a. It is
16 noted that the threshold does not subtract from the input values,
17 but it triggers an immediate "no hold" for all sample and hold
18 values less than the threshold value. This process maintains the
19 proper vector element ratios that are used for the recognition
20 process. The hold input vector values appear to be steady with a
21 short "off" period when the THMKOM 150 outputs are zero. The
22 short "off" period is provided and will be further described
23 below. With an example spike train signal applied to a delay
24 vector 288, each delay element 148 synchronizes a spike
25 representing a scalar value in synchrony at the output signal 282
26 of the delay vector 288. Signal 282 is a vector input signal
27 applied to a THMKOM 150 and signal 282 repeats for each period of

1 the spike train. Each signal 282 contains the relative spatial
2 distribution of the component objects of a super object in
3 process of recognition. Signal 282 is composed of signals 154,
4 an output of each delay element 148. Signals 154 are in
5 synchrony at one instance of time with each other, and are power
6 summed by a class prototype neuron 156. This form of nonlinear
7 summation provides an improved signal processing in a noisy field
8 of extraneous "signals". The waveform 64, or prototype
9 activation, at the output of neuron 156, will be a large
10 amplitude signal, repeating and synchronized within the period of
11 signal 54a, with a possibility of many smaller pulses occurring
12 at "random" times between the large, time shifted, synchronized,
13 repeating signals.

14 There is provided one spatial recognition vector array
15 module 58 for each output class in the preferred embodiment of
16 the invention. The temporal activations 54a, input to a spatial
17 recognition delay vector 288, are on the order of the narrow
18 output impulse of the matched filter 96 of the chaotic oscillator
19 65. The temporal activations 54a at the temporal component
20 object recognition vectors 122 are similar to the signals shown
21 in FIG. 21. A set of simple delays, or a delay vector 288, is
22 matched to the timing of the temporal activations 54a that
23 represent component objects in a specific spatial configuration.

24 The output signals 154 of all delay vector elements 148 are
25 synchronized once per temporal activation period of signal 54a,
26 both in the individual connections to a prototype neuron 156 and
27 in each input vector 282 and THMKOM 150. All simple delays

1 become the spatial recognition DVA 146 of which the output
2 signals 154 are summed by the prototype neuron 156 (FIG. 27).
3 Neuron 156 contains a dynamic threshold high enough to inhibit
4 noisy delays and to pass the highest input power sum value to its
5 output 64. Each set of spatial delay vectors 282 also drives
6 feature limiting THMKOM 150, a vector decoupling module 158 and
7 super object neural director 152.

8 The spatial recognition vector array 58 receives outputs
9 from various temporal component object recognition vector output
10 neurons 144 that are associated with the class of array 58. Each
11 neuron 144 outputs a train of pulses similar to those shown in
12 FIG. 21. One output neuron 144 contains a specific pulse train
13 similar to one of the example pulse trains in FIG. 21. The pulse
14 train contains a group of repeating pulses of different
15 amplitudes such as $t(a)$ through $t(j)$, which input into a delay
16 vector 288. The delay values (previously learned) of the delay
17 vector 288 are such that the repeating pulses are temporally
18 aligned to produce a simultaneous pulse output 282 of each delay
19 vector 288, once in each temporal period of signal 54a. The
20 simultaneous pulse output 282 of a delay vector 288 is composed
21 of signals 154, which have elements that contain values equal to
22 the varying pulse train amplitudes, thereby producing a momentary
23 multidimensional vector, which contains a direction in space,
24 used for recognition of a super object. The delayed signals 282
25 have a threshold applied by TH 280 to inhibit a hold operation
26 for all gated values less than the threshold value, and the
27 remaining signals 282 are then gated and held by THMKOM 150 and

1 decoupled by VD modules 158. The resulting signal vector is an
2 input to a super object neural director 152 to increase the
3 vector's resolution. The highest element of the vector, which
4 represents both the vector's general direction in its output
5 space and a recognition of a learned super object, is produced as
6 an output 182 of a PKOM 160.

7 The outputs of the array of PKOMs 160 are all connected
8 through associative connections 182 to super object neurons 162.

9 If the external associative connection 62 is uninhibited so as
10 to represent, e.g., an interest in an old car, then the
11 activation from the super object neuron for the old car,
12 represented by 162 object(a), passes through the enabled TPKOM
13 170, which operates in a manner similar to TPKOM 126 (FIG. 25).
14 The old car PKOM data 161, i.e., the collection of associative
15 connections 182 to old car neuron 162 object(a), is thereby
16 passed from the held vector to activate neuron 162 object(a) and
17 the old car output activation 60. It is noted that the normal
18 signal for the external associative connection 62 of interest is
19 an inhibit signal applied to each spatial recognition vector
20 array 58. This architecture reduces the burden of extraneous
21 neural information and neural activation processing in all
22 spatial recognition vector arrays 58, thus an activation of
23 interest is an uninhibit signal. The inhibit/uninhibit signal
24 can be a controlling input signal to a threshold device in that a
25 high threshold would inhibit all signal passage, while the at
26 least one uninhibit (or the removal of the inhibit) will allow
27 the threshold device to operate in a normal mode. It is also

1 noted that the architecture from the PKOM 160 array through
2 connections 182 and neurons 162 is similar to a memory vector
3 space, an active memory vector and a recognition vector
4 architecture. Each car super object is processed as described
5 above. Other super object classes, other than cars, are
6 represented in other instances of a spatial recognition vector
7 array 58.

8 In the example where the input image 42 is an old car and
9 the external associative connection 62 is uninhibited to provide
10 an activation of a "transportation" need, or an equivalent, the
11 inhibit signal will allow TPKOM 170 to pass old car activations
12 at neuron 162 object(a), to become the attentive object
13 representation 60, as shown in FIG. 1. TPKOM 170, shown in FIG.
14 27, only allows one super object activation 180 to become the
15 attentive object representation 60.

16 A second scenario is allowed when a car input image 42 is
17 foveated and no interest or associative activation 62 is active,
18 i.e., the signal remains inhibited. Then the only output of a
19 spatial recognition vector module 58 is the prototype object
20 activation 64. A third scenario is allowed if no object
21 activation 64 exists, then the input image 42 contains no known
22 class object. A fourth scenario is allowed when the pile of old
23 junk of FIG. 3 is the input image 42. The spatial configuration
24 of the component objects is not correct to represent a car and
25 only the peripheral vision object activations 66 (FIG. 11) will
26 be active. Also, the temporal signal 54a will not contain a
27 recognizable spatial configuration representing a car. Thus the

1 spatial recognition vector array 58 will not contain an output
2 signal.

3 As with the component recognition vectors 49 of FIG. 10, a
4 temporal component recognition vector 122 (FIG. 26) contains a
5 neuron 144. Each neuron 144 activates the passage of a temporal
6 signal 54a through the neuron 144 to the DVA 146 of the spatial
7 recognition vector array 58. Temporal component object
8 recognition vector 122 includes connections 277 to provide inputs
9 to a group of delay elements 148 of delay vector 288. Thus, a
10 combination of a neuron 144 and a group of recognition
11 connections 277 comprise a temporal component object recognition
12 vector 122 (FIG. 27). The active memory element 110a is shown as
13 a single active element in FIG. 26 to simplify the drawing and to
14 illustrate the concept of the temporal memory vector 51. Each
15 active memory element 110a is in reality a group of individual
16 activities of SUMs 89. The temporal component recognition
17 vectors 122 each have an input for a common threshold 184 to each
18 neuron 144. The purpose of the threshold is to inhibit minor
19 activations of the temporal component recognition vectors 122.

20 In addition to the old car attentive object representation
21 60 (FIGS. 1 and 27), the super object output representation of
22 TPKOM 170 is also connected through its associative connections
23 feedback 172 to the component object chaotic oscillators 65 of
24 the component recognition vectors assembly 48 (FIG. 11). Here
25 the association connections become a synchronizing feedback
26 signal 172 and increase the output amplitude of the temporal
27 activations 50b. The increase of the temporal activations 50b

1 then further increases the attention gain in the LGN module 45
2 only for the component object neurons that constitute the old car
3 pixel data. The associative connection feedback signal 172
4 maintains a "phase lock" on each chaotic oscillator 65 by
5 repetitively resetting its internal condition.

6 When the chaotic oscillator 65 is gated on, it is started in
7 an initial condition that is identical to the internal conditions
8 that exist in the chaotic oscillator just after a synchronization
9 activation. These conditions of synchronization produce a
10 temporal activation sequence of all relative component objects
11 that can be recognized by the spatial recognition delay vector
12 array 146. At this point in the architecture, only the old car
13 object in FIG. 2 will activate the old car super object neuron
14 162 object(a) and the attentive object representation 60 in FIGS.
15 1 and 27. The resolving ability of the prototype neuron 156
16 (FIG. 27) is low because the simple summations of the aligned
17 temporal activations carry a representation of a generalized
18 correct component configuration. The super object, with its
19 relative attentive object representation 60, has a high resolving
20 ability because its super object neural director 152 has a higher
21 sensitivity to slight variations in the component spacing. The
22 example prototype output only represents a car, while the super
23 object represents the type of car. The initial training of the
24 various neural network modules for a super object classification
25 bring the chaotic oscillators 65 of spatial image processor 10
26 into a correct synchronization, and the spatial recognition delay
27 vector array 146 into a correct temporal alignment.

1 Synchronization of the chaotic oscillators 65 is performed by a
2 characteristic of the feedback signal 172. As previously
3 described above, the temporal signal 54a is converted from a
4 serial train of information to that of a momentary
5 multidimensional vector which is held as an input signal in the
6 THMKOM 150 for a time less than the repeatable period of signal
7 54a. When the hold time of the multidimensional vector is
8 completed the input signal in the THMKOM 150 becomes a vector of
9 zero. The zero vector affects both signal 60 and feedback signal
10 172 as a "drop out" that is used to synchronize only the chaotic
11 oscillators 65 providing temporal activations for the recognized
12 super object class 60.

13 - The spatial image processor 10 shown and described herein
14 requires two training phases that occur under a single
15 application of a new super object to be learned, as long as all
16 component objects were previously learned. The first phase is a
17 chaotic adaptive resonant learning of the spatial recognition
18 delay vector array 146 under an instance only when it is the
19 first to be learned in its class. The second phase is the
20 learning for the initial condition activation of the chaotic
21 oscillators 65 which forces each-related component chaotic
22 oscillator 65 into a closer "synchrony" with each other. The low
23 level component recognition vector array 49 and temporal
24 component recognition vector array 122 must be independently
25 learned from the new object to be learned.

26 To train a low level component object, its input image 42
27 can be placed anywhere on the input array 40 to produce a

1 component memory vector 63 (FIG. 10) and a temporal memory vector
2 51 (FIG. 26) in their respective output space 59, 140. To train
3 a temporal component object recognition vector in array 49, a set
4 of normalized value connections 77 are placed between an
5 unlearned output neuron 74a in the array of temporal component
6 recognition vectors 122 and each element of its active temporal
7 component memory vector 51.

8 The component recognition vector connections 79 (FIG. 10)
9 are also trained as indicated above, except that a set of
10 normalized component recognition bi-directional connections 79
11 are connected between an unused neuron 174 of component object
12 recognition module 48 and each element of the memory vector 63
13 while the low level component object input image 42 is applied.
14 A component recognition vector neuron 67 allows an active
15 recognition signal to feedforward along one path to enable a
16 chaotic oscillator 65 and a feedback signal to back track
17 parallel along the same path as the active signal. The
18 feedforward active signal enables the feedback path at each
19 neural junction.

20 The temporal activations of a chaotic oscillator 65 (FIGS.
21 11 and 11A) are initialized during a low level component training
22 of a component recognition vector 49 and connections. The
23 matched filters 96 of each uninitiated chaotic oscillator 65 have
24 random matched filter connections and have a random activation
25 pattern to be the chaotic oscillator's "initial condition". A
26 set of initial conditions is defined as variables/potentials
27 assigned to each neuron and delay line cells where the initial

1 conditions are values equivalent to a free running nonlinear
2 chaotic oscillator frozen in an instant of time. At the time a
3 chaotic oscillator 65 is initially activated by its component
4 recognition vector 49, the matched filter 96 senses its highest
5 output activation over the sequence of patterns and when an
6 identical activation occurs for the second time, the matched
7 filter 96 assumes connection values equal to the chaotic
8 oscillator's activation pattern of nonlinear neurons 96a of
9 matched filter 96. A matched filter 96 is similar to the initial
10 conditions and is defined as containing connection values from an
11 instant in time of neuron values where each connection assumes
12 its neuron's activation value at said instant of time. The
13 training of each low level component object is processed as
14 above.

15 The training of a new attentive object class is usually
16 accomplished by using a basic form of the object containing all
17 essential components because the first object also approximates
18 the prototype class, but it is not required for it to be a basic
19 form. Special initial conditions are required for a new
20 attentive object class for the spatial recognition vector array
21 58 of FIG. 27. Assuming an example of an old car as the training
22 image 42, these initial conditions are:

- 23 (1) The neuron 156 operates at a low threshold;
- 24 (2) There are no temporal component recognition vector
25 output connections 277 to the spatial recognition delay vector
26 array 146;

27

1 (3) Each untrained delay vector element 148 is set for a
2 random delay;

3 (4) "Prewired assemblies" 176 of grouped delays 288, THMKOM
4 150, VD 158, super object ND 152 and PKOM 160 modules exist as a
5 set of independent modules with a priori unit connections between
6 each modules;

7 (5) Each delay output signal 154 is connected to neuron 156
8 with a unit value connection;

9 (6) The super object old car neuron 162 object(a) input
10 connections 182/161 do not exist;

11 (7) The associated feedback connection 172 does not exist;

12 (8) The external class associative connection 62 is
13 uninhibited because the object to learn is an object of interest;

14 (9) All remaining connections are as represented in the
15 spatial recognition vector module 58;

16 (10) Th module 280 has a temporary training connection (not
17 shown) to object (a) neuron 162; and

18 (11) A new attentive object to be learned places its input
19 image on the input array 40.

20 In the first phase of training, the various component object
21 recognition vectors 49 activate their chaotic oscillators 65 and
22 matched filters 96 to produce a sequence of temporal data 104,
23 similar to one of the impulses per period shown in FIG. 15.
24 Temporal data 104 returns along the feedback path through retina
25 52 and memory processor 56 to the temporal component recognition
26 vectors 122, as previously described. Upon a Hebbian-like
27 activation, each one of the active temporal component recognition

1 vectors 122 becomes directly connected by unit connections 277 to
2 a delay vector 288 in the DVA array 146, as neural module 58 is
3 active for learning, and immediately neuron 156 becomes activated
4 with temporal pulses from signal 54a. Each chaotic oscillator 65
5 is similar to each other but contains random initial condition
6 starting values and different immediate activation patterns.
7- Thus they have similar repeated pattern periods, which generate
8 varied temporal signals that produce repeated varied rising of
9 power summations in neuron 156 caused by the initial random
10 delays and the input chaotic temporal activations. Each time the
11 neuron 156 senses a maximum peak in summation, it produces a
12 momentary output 64 and readjusts its threshold to its new peak
13 in a period of 54a. In this training mode only, and upon the
14 first repeated maximum peak of neuron 156, the TH module 280
15 learns an approximation of the timing period for an end of the
16 hold time and provides a synchronizing "drop out" as discussed
17 below. As a function of the changing output sequences from
18 neuron 156, while the hold timing stabilizes through neuron 156,
19 the TH module 280 provides a "drop out" simulation to TPKOM 170
20 previously enabled by the external connection 62. The "drop out"
21 occurs between the hold time and a period of signal 54a. Also,
22 upon the initial synchronizing "drop out" activity, the
23 activations between the TPKOM 170 output and the associative
24 active component chaotic oscillators 65 generate Hebbian
25 associative feedback unit connections 172 between the TPKOM
26 active output 170 and each active chaotic oscillator 65. Upon
27 the generation of the feedback connections 172, each time neuron

1 162 is at a peak, the TH module 280 momentarily "drops out" its
2 activity and the TPKOM output synchronizes the oscillators 65 by
3 resetting the oscillators' initial conditions. The temporal
4 activations at the spatial recognition delay vector array 146
5 (FIG. 27) start to repeat in a deterministic fashion. The
6 individual delays are further adjusted in time to increase the
7 output of neuron 156. When the delay error and the TH module 280
8 hold time error both approach an acceptable minimum, without a
9 duplication in delay values in any one of the group of delay
10 vectors 288, the training is halted for that assembly. As the
11 output 64 of 156 increases during this training, so does its
12 threshold to insure that only one peak output is convergent.
13 When the delays for all assemblies are convergent and their
14 output activations correlate through to PKOM 160, the old car
15 super object normalized input connections 161 are generated.
16 Thus each of the concurrent active PKOM 160 has one output (FIG.
17 27) for the object learned and activates the super object old car
18 neuron 162 object(a). At the same instant of time, the training
19 connection from TH module 280 is removed. If required, training
20 is continued to further optimize the delays and hold values.

21 The object trained now becomes the prototype object, becomes
22 the first super object (a) neuron and becomes the attentive
23 object representation 60. The sequence of the first phase is
24 complete and training continues into the second phase without
25 stopping if it is found to be required.

26 In the second phase, the chaotic oscillator's exact
27 activation pattern is noted at the instant of the matched

1 temporal data 104 output activation and is used to rematch the
2 connections of network matched filters 96. The reason for a
3 rematching is that a synchronized chaotic oscillator near its
4 initial condition actuation alters its patterns slightly from
5 that of its initial free running mode and that the best match of
6 the random connections 96 may not be exact. The chaotic
7 oscillator's matched filter 96 is rematched at the time when its
8 peak activation occurs by resetting the matched filter connection
9 values equal to the chaotic oscillator's exact activation
10 patterns and resetting the matched filter 96 threshold to a value
11 relative to its new matched output value. This does not alter
12 the timing of the chaotic oscillator 65. The above training
13 phases allow an "immediate" (within one cycle) spatial
14 recognition of a super object of interest when its input image is
15 instantly presented on the input array 40. Other super object
16 neurons 162 of the same class are trained by repeating the
17 application of a new normalized connection set 161 from the
18 active PKOM 160 outputs 182 to the new super object neuron 162.
19 A new class of super objects requires another spatial recognition
20 vector array 58 and training of its component recognition vectors
21 49, then a repeat of the two phases.

22 There is thus provided a spatial image processor 10 that is
23 capable of discriminating between two groups comprised of
24 identical components in two different spatial configurations.
25 The spatial image processor 10 increases its sensitivity or
26 attenuation to an object of interest in a field of more than one
27 object and invariantly recognizes an object in retina

1 translations. The processor recognizes a partially hidden object
2 when the object is incomplete or split, and also recognizes one
3 object in a field of many different objects and/or of different
4 object sizes.

5 The description of the spatial image processor 10 has been
6 presented using component objects in a spatial configuration of a
7 super object. The component objects do not have to be as complex
8 as used in the examples herein. They can be of a lower set of
9 basic geometric shapes or primitives (a set of the smallest and
10 discernible parts of a visual scene) out of which any super
11 object can be constructed.

12 The sensitivity of the spatial image processor 10 invention
13 can be improved or simplified by interchanging the PMKOM, MKOM,
14 PKOM, and KOM with or without thresholds and/or with other
15 constructed neural network modules depending upon the design
16 and/or purpose of the embodiment for the invention. These
17 changes may increase the efficiency of the attentive super object
18 and at the same time affect "non attentive" component objects to
19 be reduced below the applied thresholds, thereby being eliminated
20 from all recognitions as their effective contrasts are zeroed.

21 Referring now to FIGS. 28-30, a second embodiment of the
22 spatial image processor is shown as 10'. As in FIG. 1, FIG. 28
23 shows the overall architecture of spatial image processor 10'.
24 In comparison with FIG. 1, spatial image processor 10' combines
25 the two memory processors 46 and 56 of the first embodiment into
26 a single memory processor 46'. Memory processor 46' is
27 configured in the same manner as processors 46 and 56 of the

1 first embodiment, including the complex neurons as described
2 previously for the first embodiment. The complex neurons of
3 processor 46' enable the feedback signal back to the retina,
4 enable the spatial temporal signal forward for super object
5 recognition through the same path as the pixel data and process
6 the pixel signal forward for component recognition. The "image
7 signal" and/or its derivatives pass three times through the
8 memory processor 46' and component recognition vectors assembly
9 48'.

10 Three signals, 44', 50' and 54a', will be used to describe
11 the signal paths through spatial image processor 10'. These
12 signals correspond to signals 44, 50 and 54a, respectively, of
13 signal processor 10 of FIG. 1. Standard pixel data 44' travels
14 through LGN 45' to the component object recognition vectors and
15 activates one or more generators 65' from a component temporal
16 generator array (FIG. 30) within component recognition vectors
17 assembly 48'. It can be seen that the component temporal
18 generators 65' correspond to chaotic oscillators 65 of FIG. 11.
19 A generator 65' becomes active and applies a sequential pulse as
20 a source for the temporal signal 50'. Each active component
21 recognition vector 49' gates its temporal activation at a
22 specific time within a cycle of repeat temporal activations, as
23 controlled by temporal sequence timer 49a. Signal 50' follows
24 the feedback path, enabled by signal 44', back to gradient
25 temporal spatial retina 52' and LGN 45'.

26 Temporal signal 50' (as signal 50a') causes LGN 45'
27 attention and retina spatial distributions as described in

1 relation to LGN 45 of FIGS. 1 and 5, providing signal 44a' to
2 gradient temporal retina 52'. (In the embodiment of FIG. 1,
3 corresponding signal 44a of LGN 45 is provided to memory
4 processor 46 as signal 44b and to retina 52 as signal 44c.) The
5 gradient temporal retina 52' (FIG. 29) operates generally in the
6 manner of retina 52. However, instead of signal 50'
7 (corresponding to signal 50b of FIG. 12) activating neurons in
8 the temporal retina 112', signal 50' has a gradient applied to it
9 at gradient retina 112a. The activations from signal 50' through
10 gradient retina 112a to temporal retina 112' are different in
11 amplitude depending upon how far from the fovea center the
12 activated neurons 116a are. Thus, the gradient temporal retina
13 52' must sense the image to be recognized at its fovea center,
14 i.e., the new attentive object to be learned is foveated by
15 placing the centroid of its input image at the center of the
16 input array 40'.

17 The temporal and spatial retinas 112' and 114' operate in
18 the manner described for retinas 112 and 114, respectively, to
19 provide signal 54a'. The temporal spatial signals 54a' are now
20 combined with the pixel data 44' and, being enabled at each
21 neuron, ride through the positive path of signal 44' to the
22 component temporal generators 65' of component recognition
23 vectors assembly 48'. The component recognition vectors assembly
24 48' has two outputs. The first is the output 104' of component
25 temporal generators 65' for signal 44' that enables signal 50' as
26 described previously. The second is the output 122' that enables
27 signal 54a'. It is seen from FIG. 30, that output 122' results

1 from recognition vectors 49' combined with signal 54a' merely
2 passing through assembly 48'. By merely passing through assembly
3 48', the path for signal 54a' from gradient temporal retina 52',
4 through processor 46' and assembly 48' is analogous to the path
5 for signal 54a from retina 52 through processor 56 in the first
6 embodiment of FIG. 1. Output 122' feeds the super object and
7 temporal array 58' to produce attentive object representation
8 60', prototype object activations 64' and associative connections
9 feedback 172', in a manner similar to that described for array
10 58, representation 60, activations 64 and feedback 172,
11 respectively, of FIG. 1. While the super object and temporal
12 array 58' is similar to spatial recognition vector array 58 of
13 FIG. 1, array 58' extends the external inhibit/activate signal
14 62' to its TH module to further reduce unnecessary signal
15 processings as discussed for TPKOM 170 of FIG. 27.

16 Thus, it is seen that the spatial image processor of either
17 embodiment senses the relative Euclidean spacing of component
18 objects that make up a super object's virtual image, so as to
19 recognize the super object and its classification without regard
20 to the image size. The information of the relative Euclidean
21 spacings of the component object-images is carried with each
22 temporal component object activation. Therefore, a partial
23 obstruction of the super object image does not impede the
24 recognition of the super object as the remaining visible
25 component objects will carry correct and recognizable geometric
26 configuration information. The component objects of a super
27 object, in a different spatial configuration from that learned,

1 are discriminated from recognition by their spatial orientations.
2 The spatial image processor uses a low level attention feedback
3 from each recognized component object in an input scene to
4 enhance the sensitivity of each known component object signal
5 path and to reduce the unimportant parts of the scene. If there
6 exists an interest (external input) in a super object in the
7 scene, then a higher level feedback attention further enhances
8 the processed signal carrying the super object and reduces all
9 other processed signals in the input scene.

1 Attorney Docket No. 77346

2
3 A SPATIAL IMAGE PROCESSOR

4
5 ABSTRACT OF THE DISCLOSURE

6 A spatial image processor neural network for processing
7 image data to discriminate between first and second spatial
8 configurations of component objects includes a photo transducer
9 input array for converting an input image to pixel data and
10 sending the data to a localized gain network (LGN) module, a
11 parallel memory processor and neuron array for receiving the
12 pixel data and processing the pixel data into component
13 recognition vectors and chaotic oscillators for receiving the
14 recognition vectors and sending feedback data to the LGN module
15 as attention activations. The network further includes a
16 temporal spatial retina for receiving both the pixel data and
17 temporal feedback activations and generating temporal spatial
18 vectors, which are processed by a temporal parallel processor
19 into temporal component recognition vectors. A spatial
20 recognition vector array receives the temporal component
21 recognition vectors and forms an object representation of the
22 first configuration of component objects.

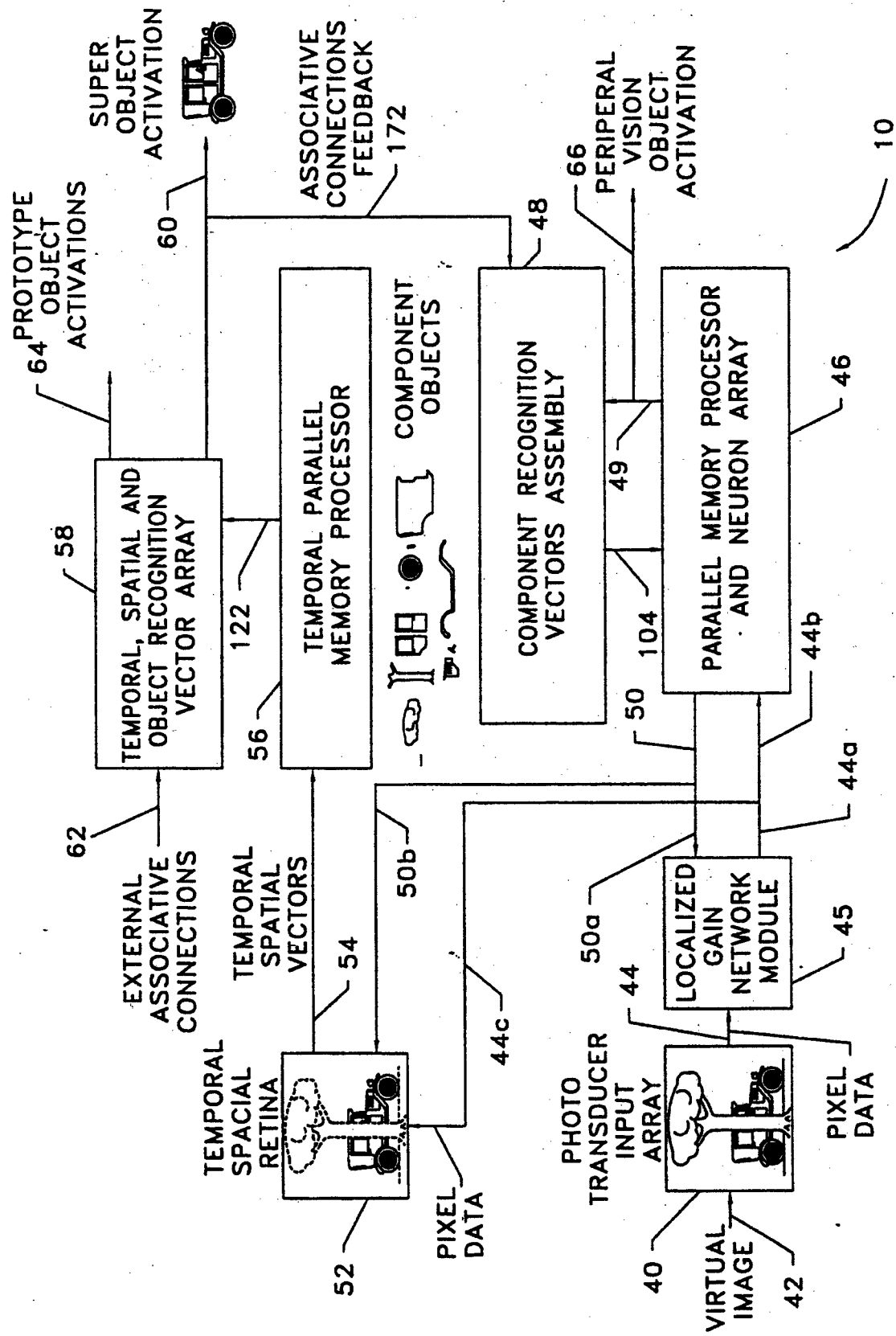
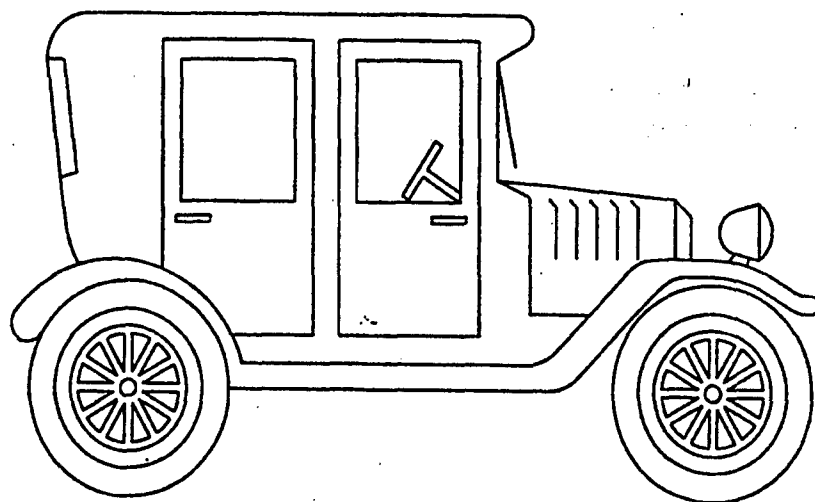
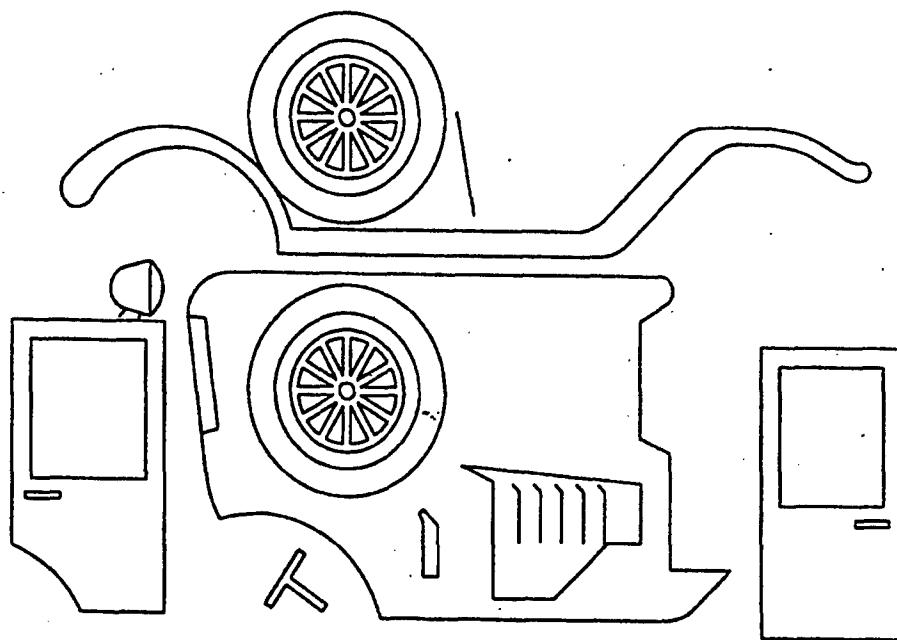


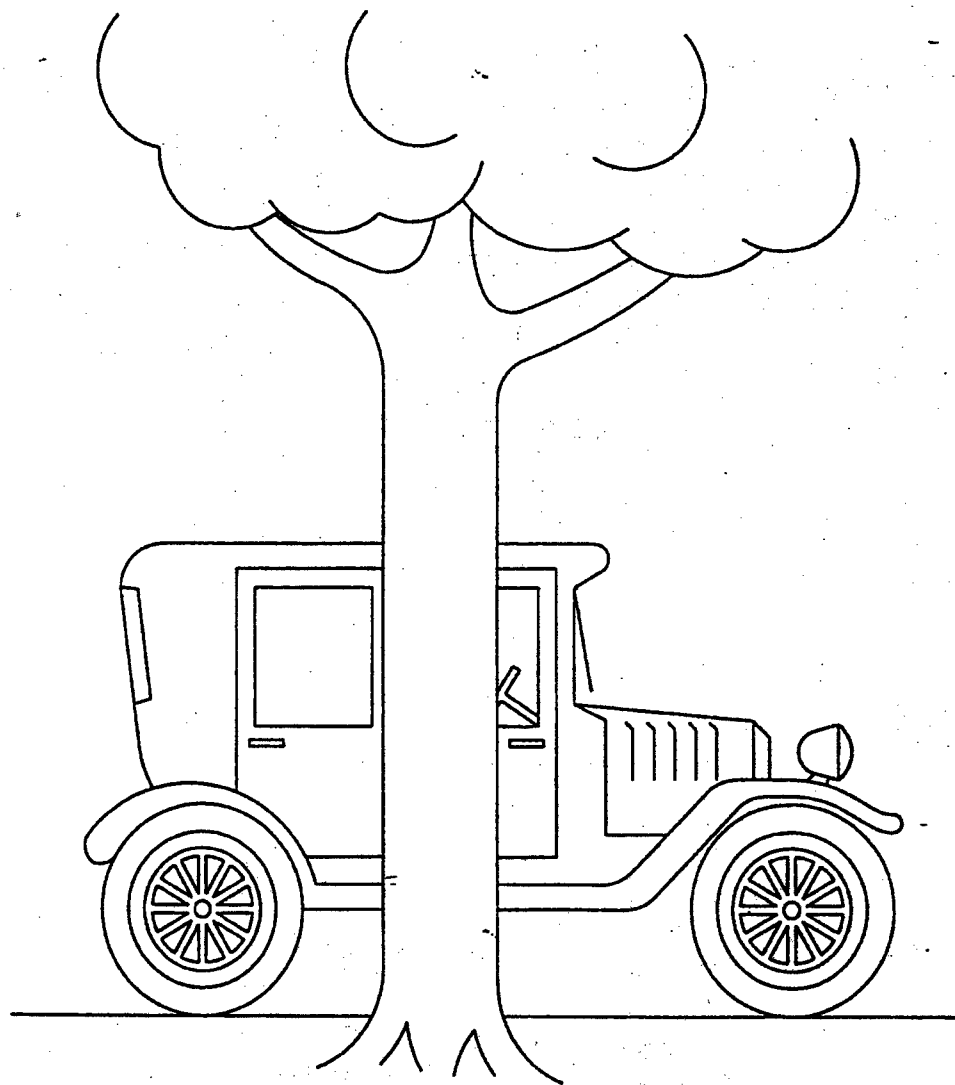
FIG. 1



OLD CAR
FIG. 2



PILE OF OLD JUNK
FIG. 3



AN OLD CAR IMAGE SEPARATED BY A TREE

FIG. 4

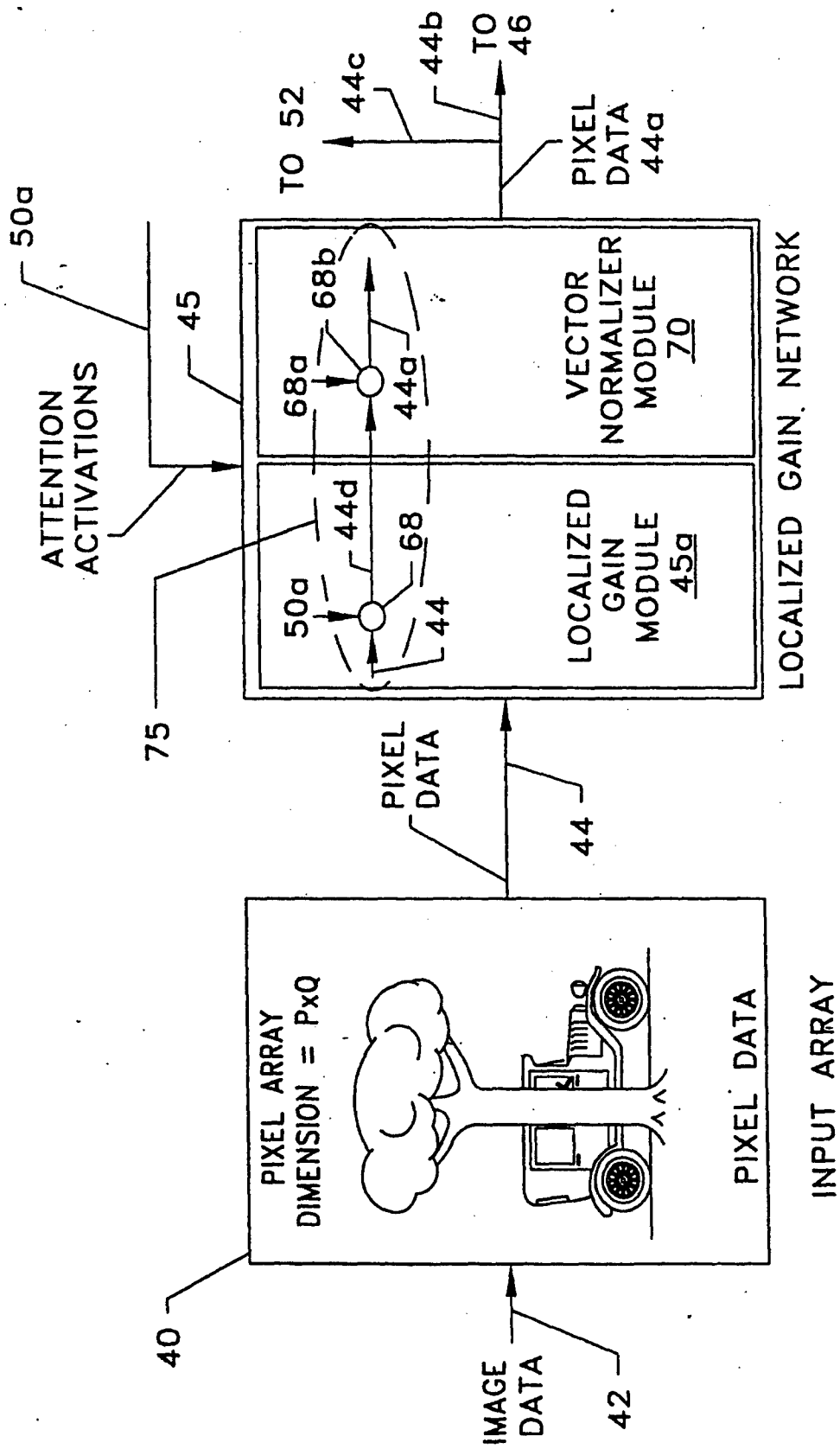


FIG. 5

FIG. 6

The diagram illustrates a multi-layer neural network architecture. At the top, a dashed box labeled 46 contains a 'NEURON ARRAY 67' (104) and a 'COMPONENT MEMORY VECTOR SPACE' (59). Below this, a 'VIRTUAL COMMON FEATURE SPACE' (104) is shown. The network consists of several layers of processing units:

- Input Layer:** 'TO TEMPORAL SPATIAL RETINA (52)' provides 'PIXEL DATA FROM LGN MODULE (45)' (50) to the 'RETINA ARRAY (dim PxQ)' (80).
- Feature Extraction Layer:** The 'RETINA ARRAY' (80) outputs to a 'W D N' block (84b), which then feeds into a 'V D' block (84). The output of this block is a 'NEURAL DIRECTOR (1,s)' (84).
- Feature Space Layer:** The 'VIRTUAL COMMON FEATURE SPACE' (104) contains four 'SUM' blocks: $SUM(1,r)$, $SUM(2,r)$, $SUM(,)$, and $SUM(n,r)$. Each 'SUM' block receives inputs from the 'NEURAL DIRECTOR' layer and outputs to a corresponding 'FTPKOM' block: $FTPKOM(1,s)$, $FTPKOM(2,s)$, $FTPKOM(,)$, and $FTPKOM(n,s)$.
- Output Layer:** The 'FTPKOM' blocks output to a series of 'NEURAL DIRECTOR' blocks: $NEURAL DIRECTOR(1,s)$, $NEURAL DIRECTOR(2,s)$, $NEURAL DIRECTOR(,)$, and $NEURAL DIRECTOR(n,s)$.
- Final Output:** The 'NEURAL DIRECTOR' blocks output to a 'MULTI-LAYER NEURAL DIRECTORS' block (72), which produces the final output (74).

Key components and connections are labeled with reference numerals: 46, 49, 50, 52, 55, 59, 67, 72, 74, 79, 80, 82, 84, 84b, 86, 88, 94, 98, 104.

THE RETINA OUTPUT FEATURE VECTOR
IS A VECTOR OF VECTORS, THERE ARE
 s VECTORS OF r DIMENSIONS EACH.
FEATURE VECTOR OUTPUT DIMENSION
IS $s \times r$

DIMENSION $s = P \times Q$
EACH NEURAL DIRECTOR HAS
 r OUTPUT ELEMENTS

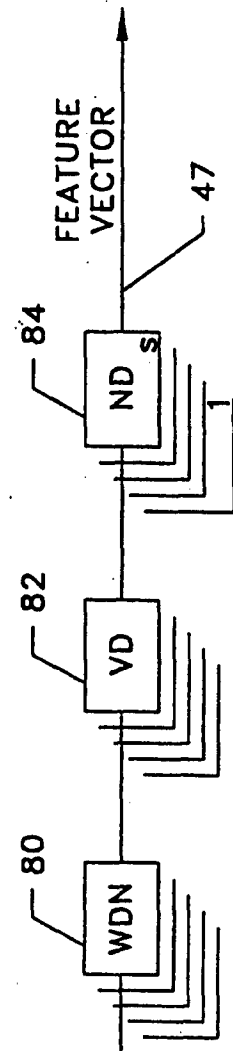
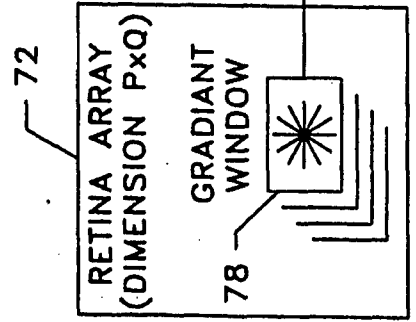
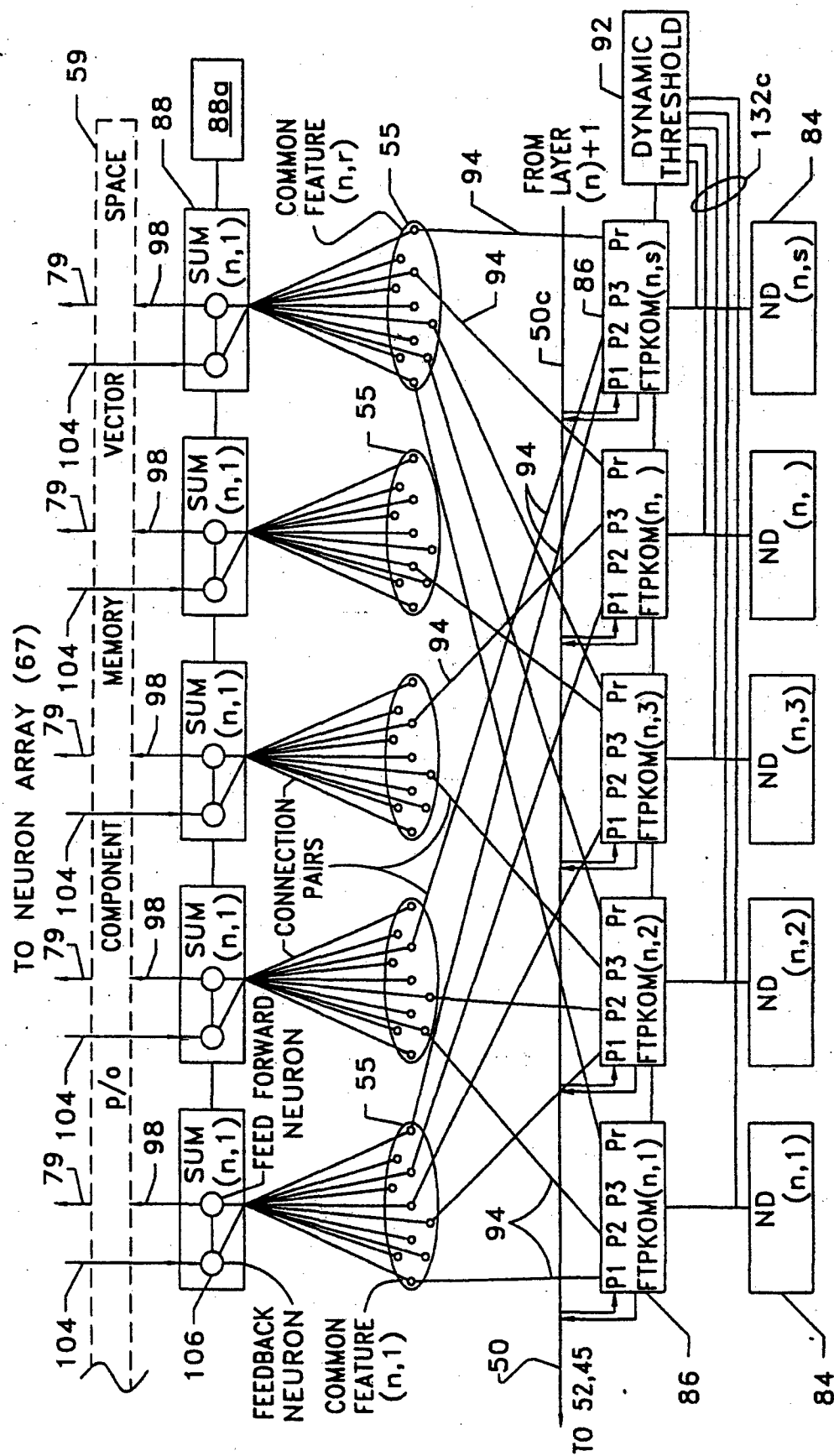


FIG. 7



86

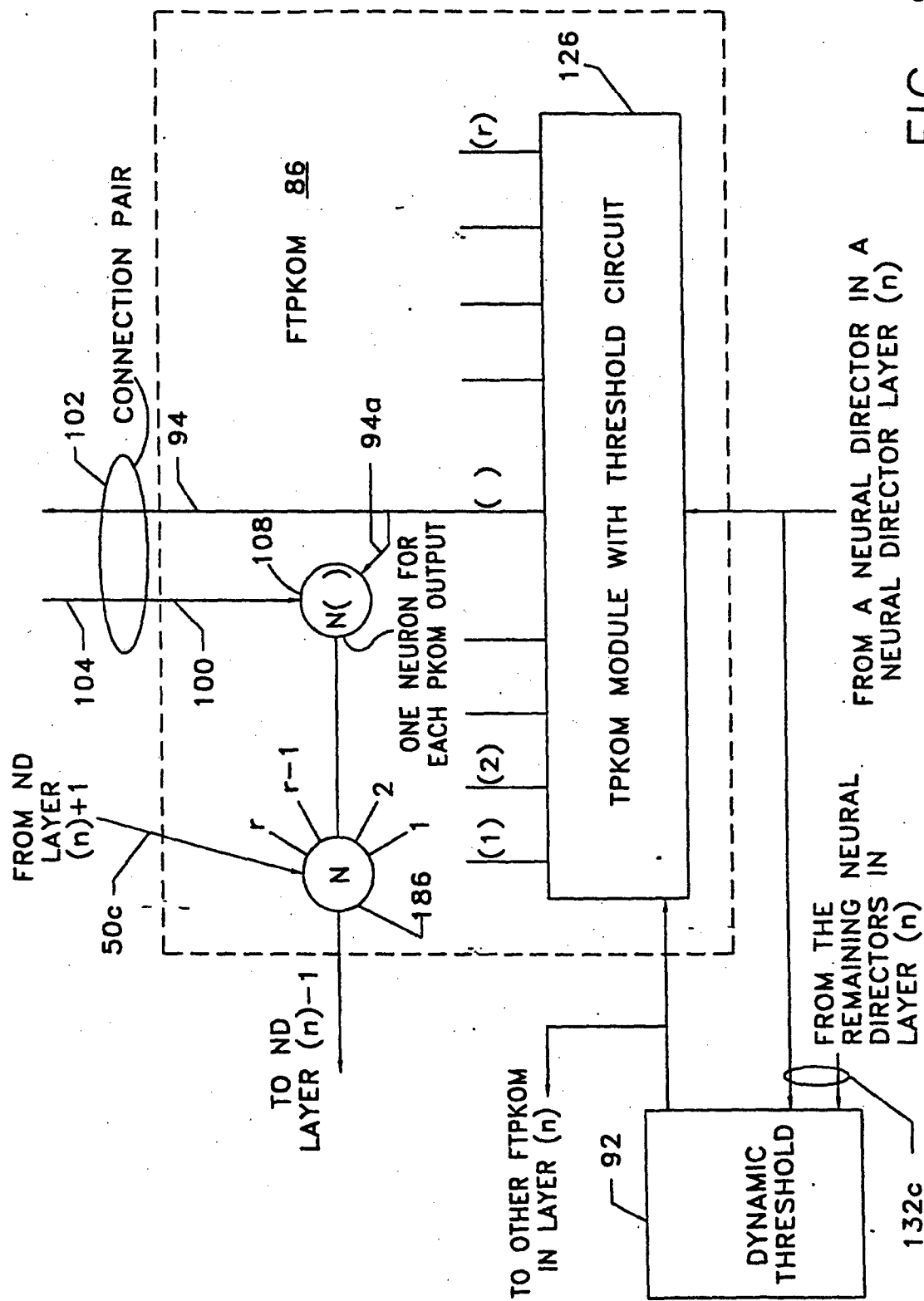


FIG. 9

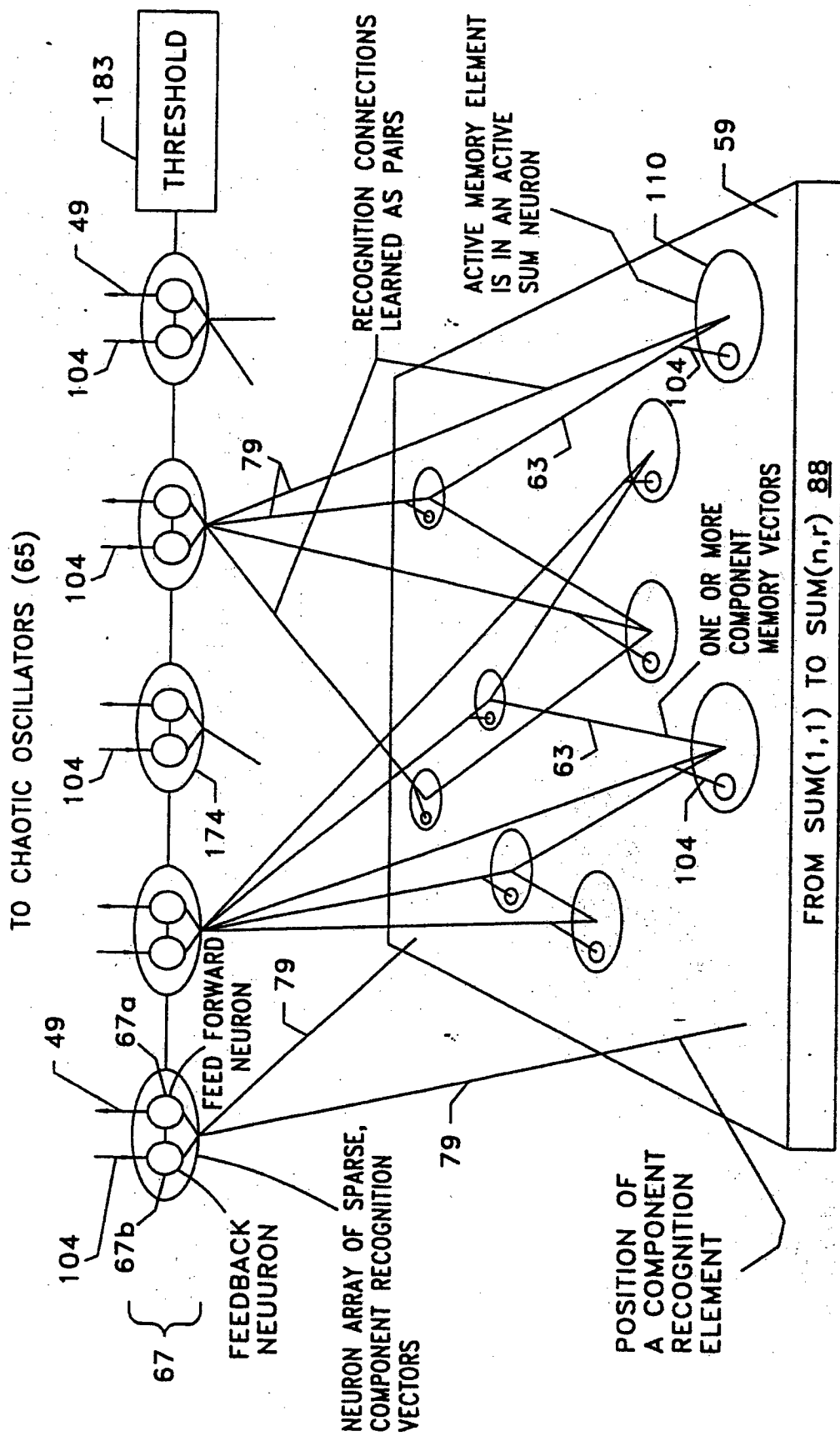


FIG. 10

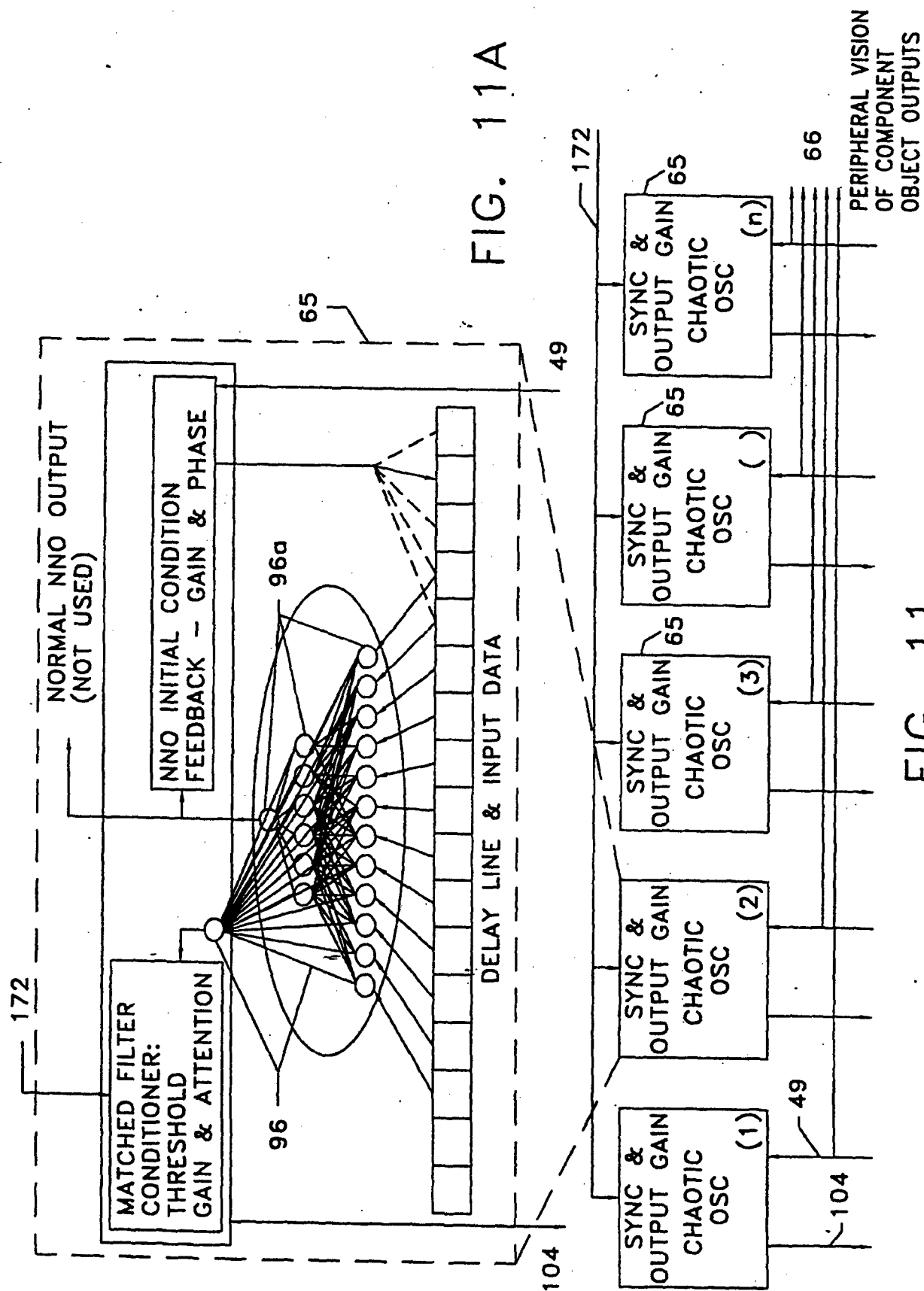
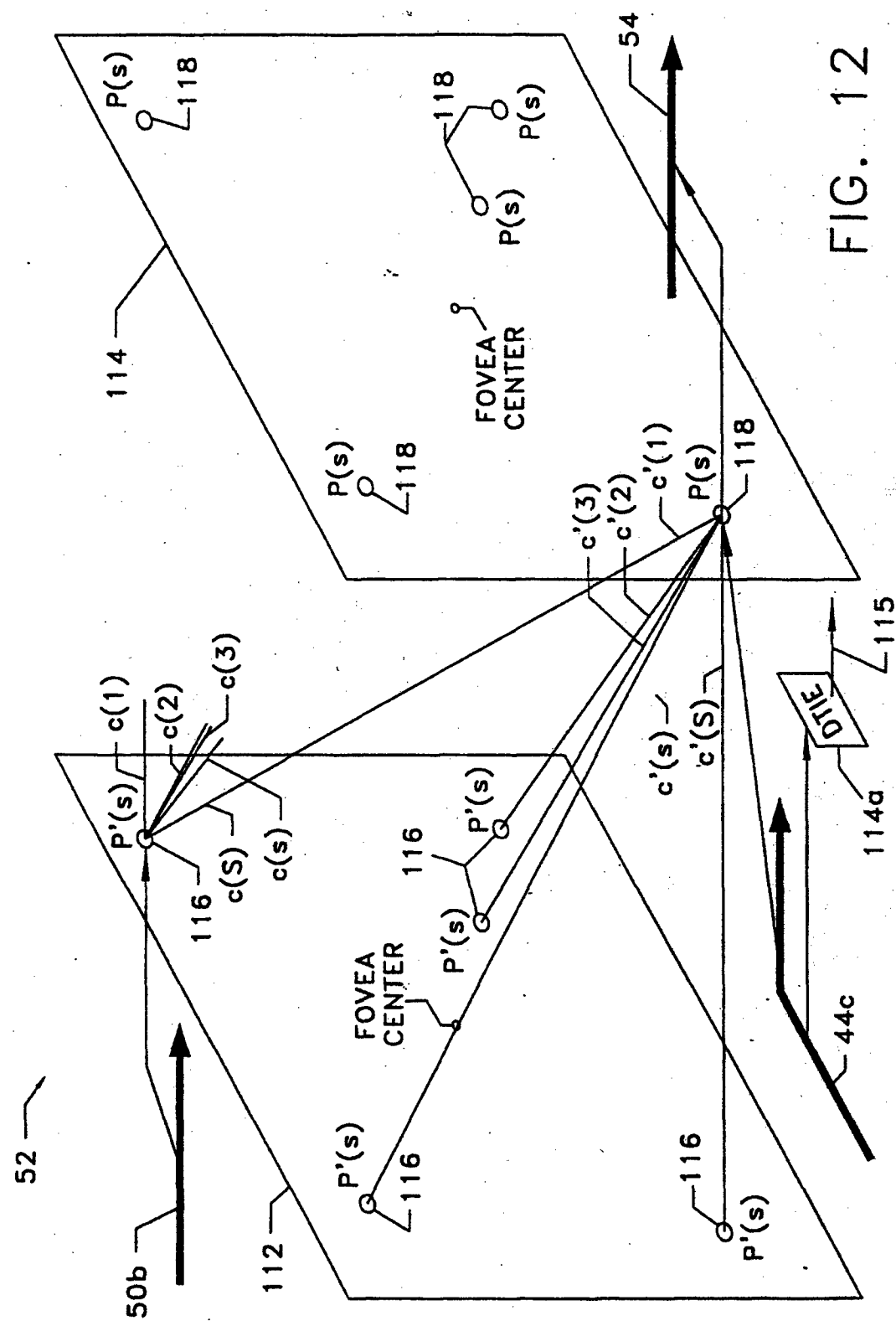


FIG. 11A

FIG. 11



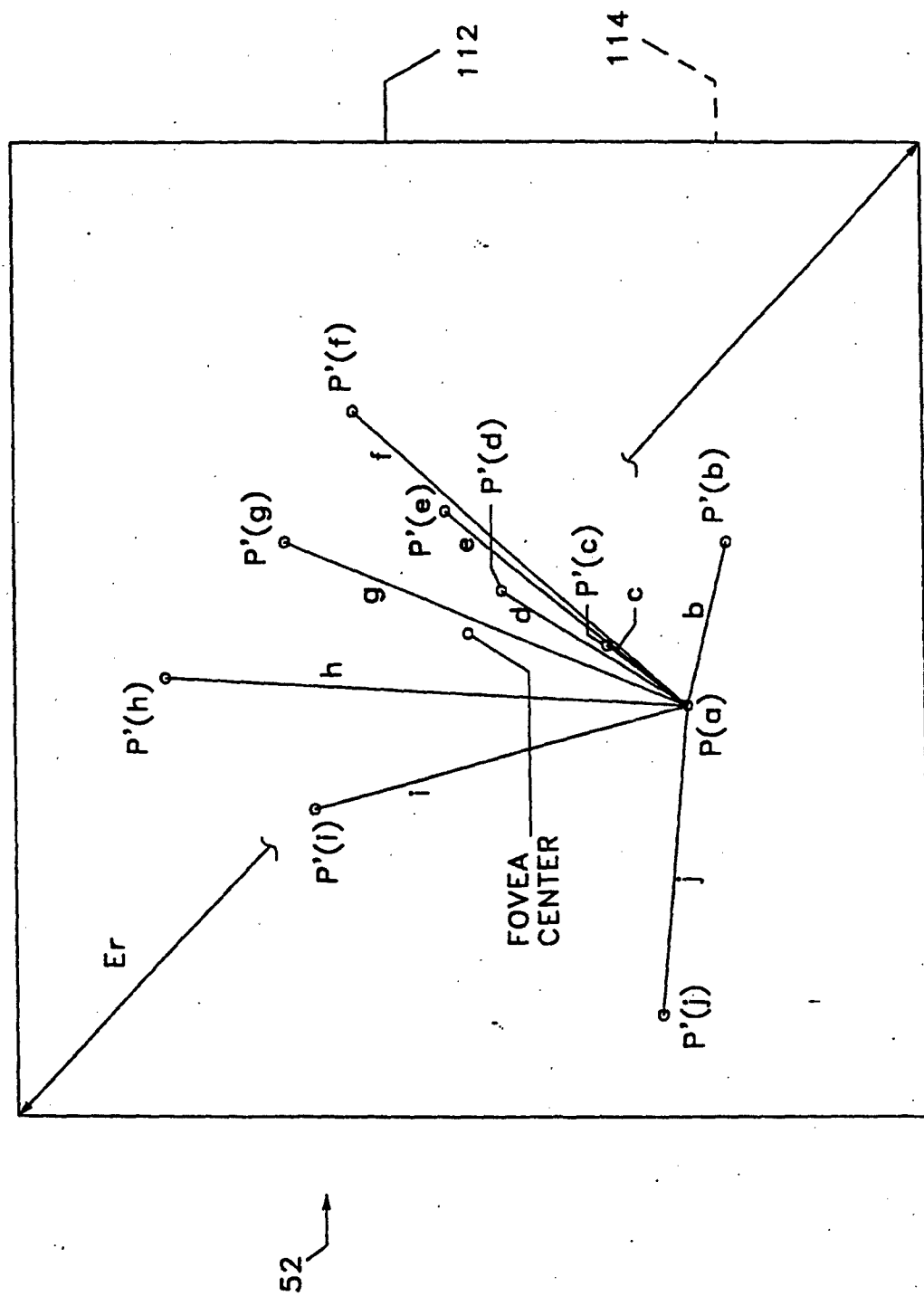
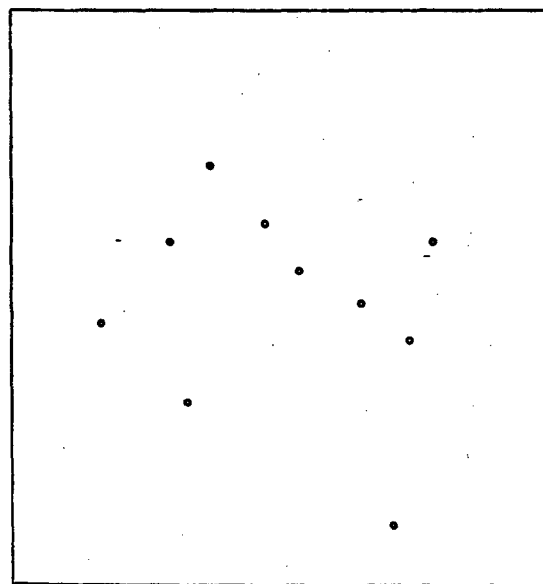
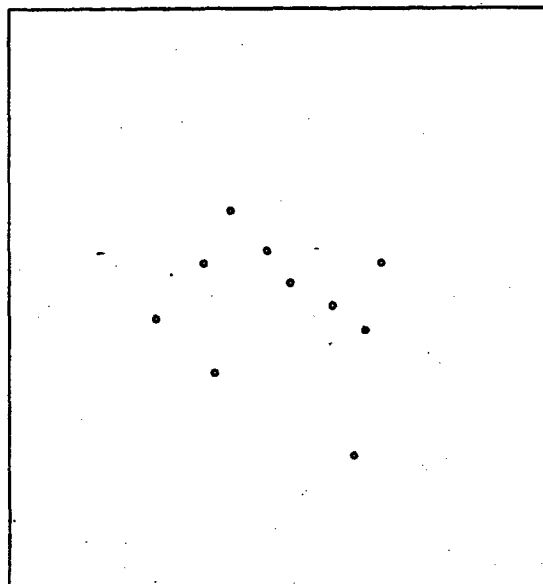


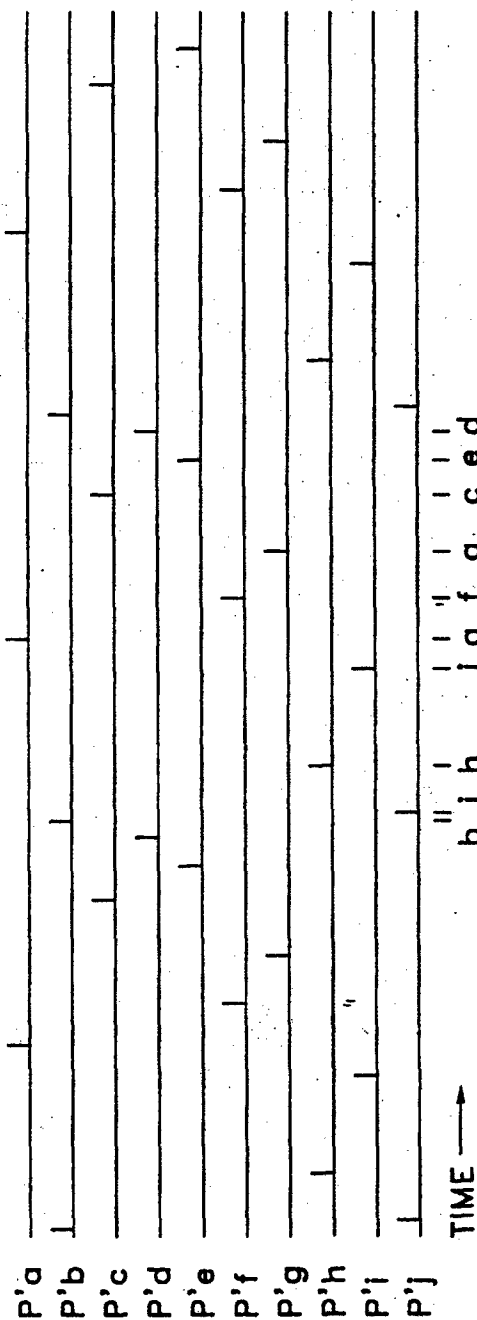
FIG. 13



INPUT IMAGE

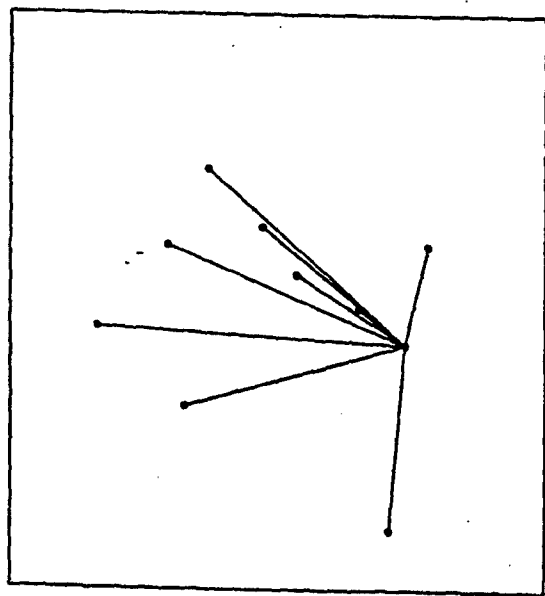


DISTANT INPUT IMAGE

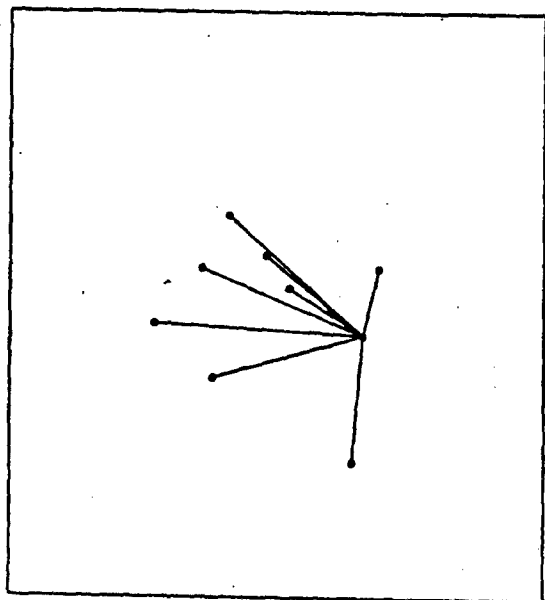


COMPONENT OBJECT TEMPORAL PULSE ACTIVITIES 50b

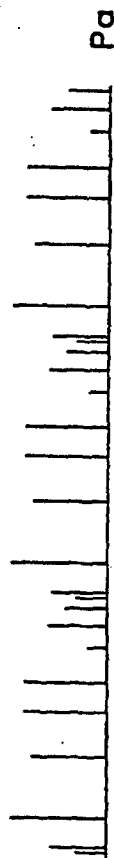
FIG. 14



CONNECTION SET α

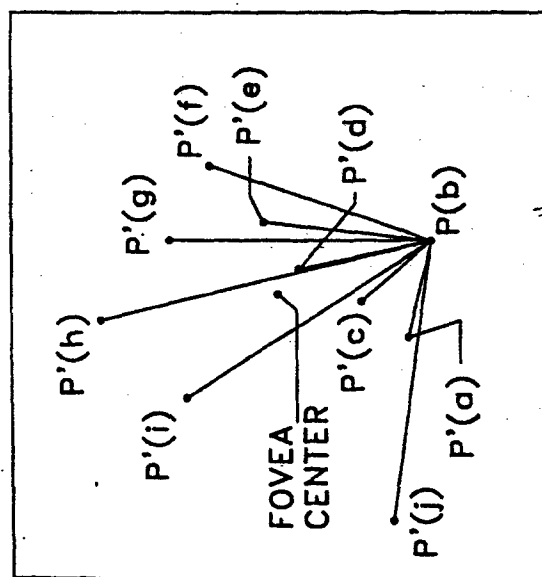


CONNECTION SET α'

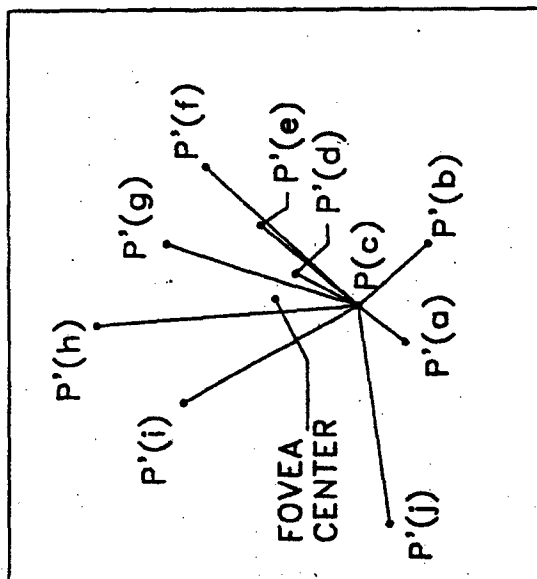


TEMPORAL SPATIAL DATA ACTIVITIES 54 α

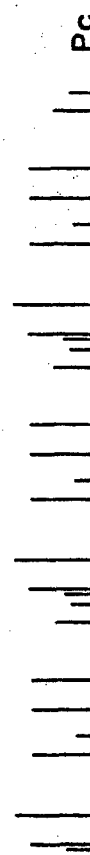
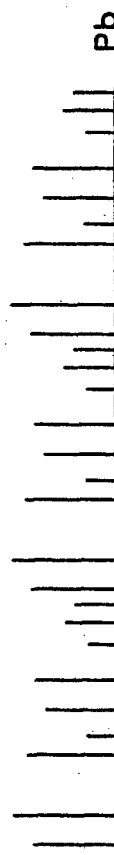
FIG. 15



CONNECTION SET b

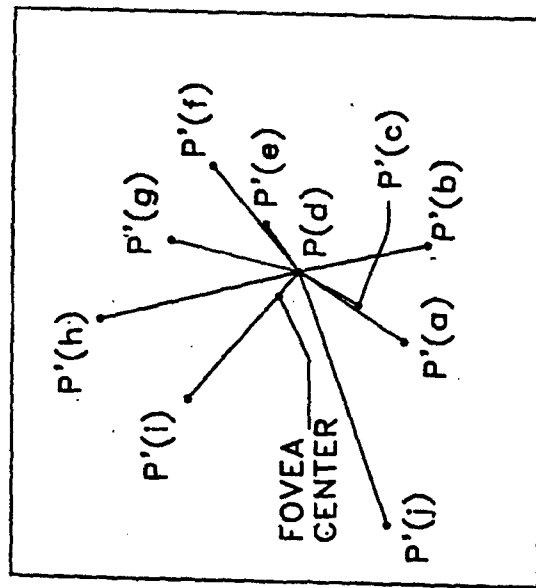


CONNECTION SET c

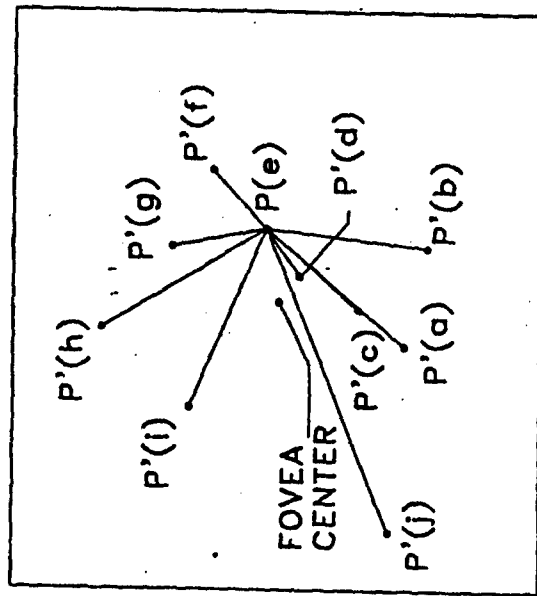


TEMPORAL SPATIAL DATA ACTIVITIES 54a

FIG. 16



CONNECTION SET d

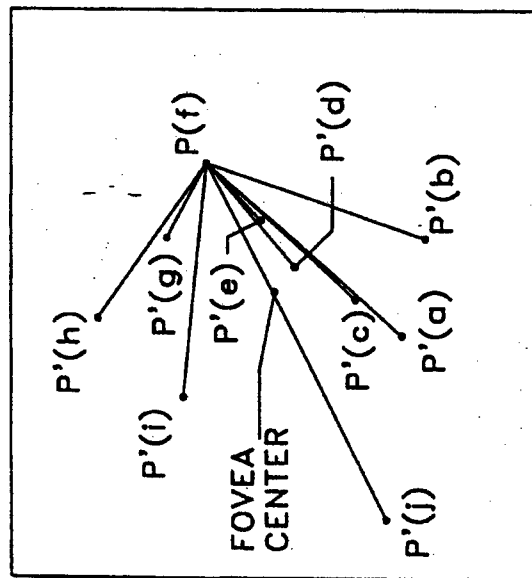


CONNECTION SET e

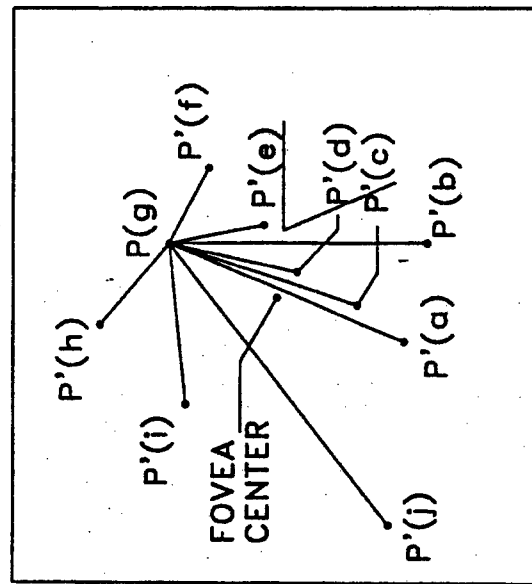


TEMPORAL SPATIAL DATA ACTIVITIES 54a

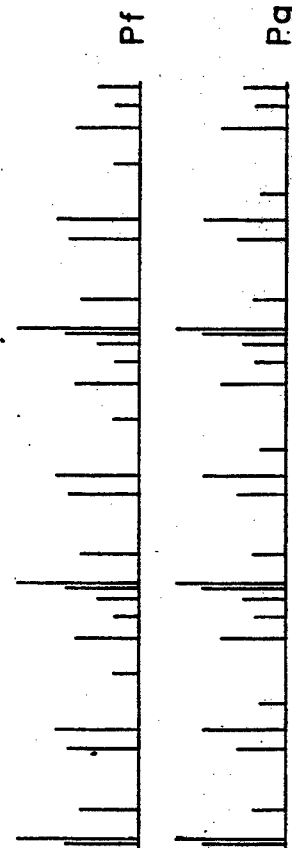
FIG. 17



CONNECTION SET f

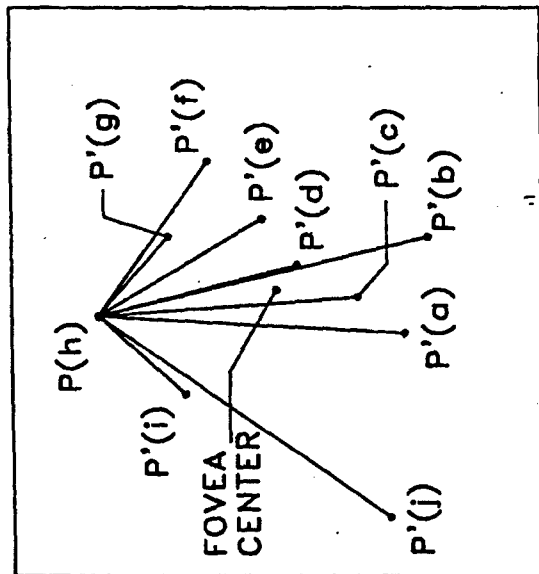


CONNECTION SET g

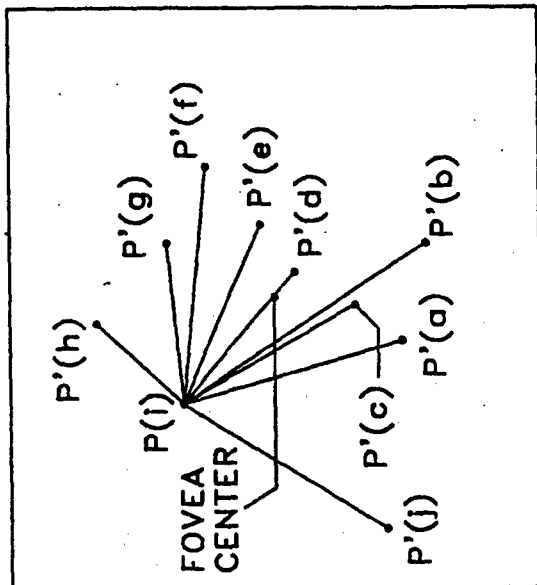


TEMPORAL SPATIAL DATA ACTIVITIES 54a

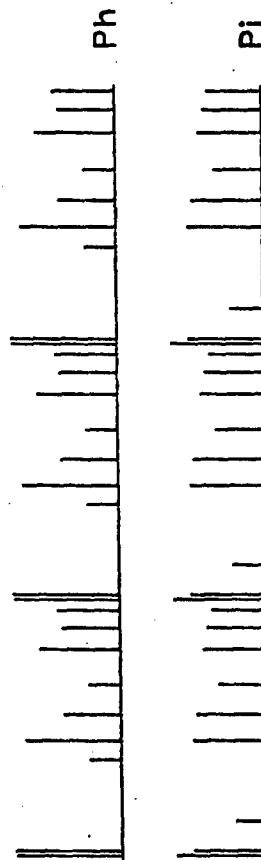
FIG. 18



CONNECTION SET h

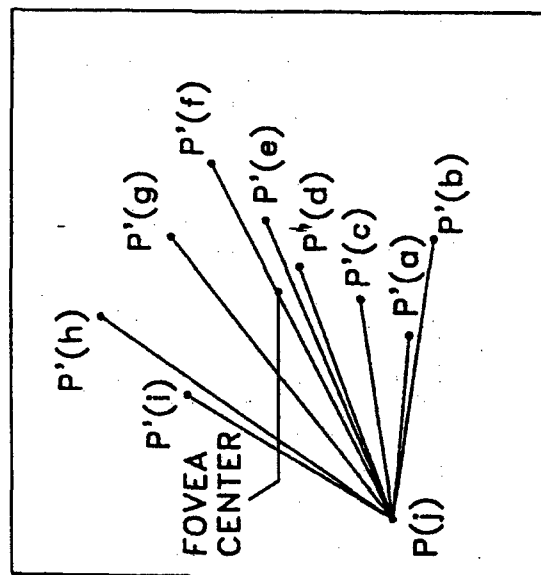


CONNECTION SET i

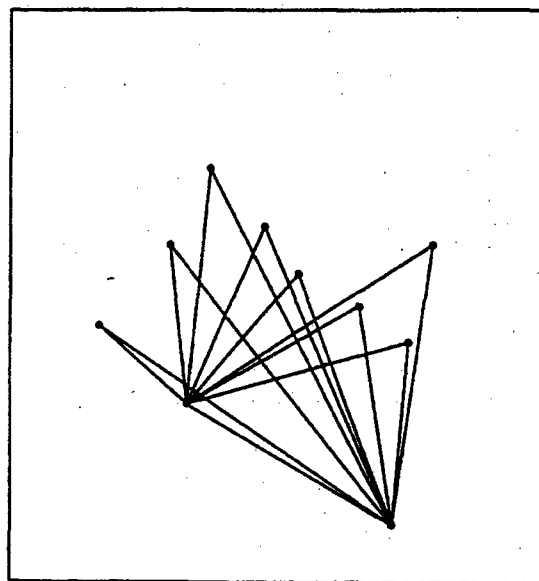


TEMPORAL SPATIAL DATA ACTIVITIES 54a

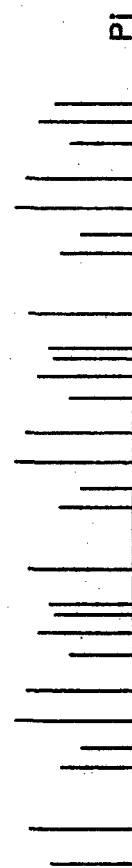
FIG. 19



CONNECTION SET J



CONNECTION SETS I & J SUPERIMPOSED



TEMPORAL SPATIAL DATA ACTIVITIES 54a

FIG. 20

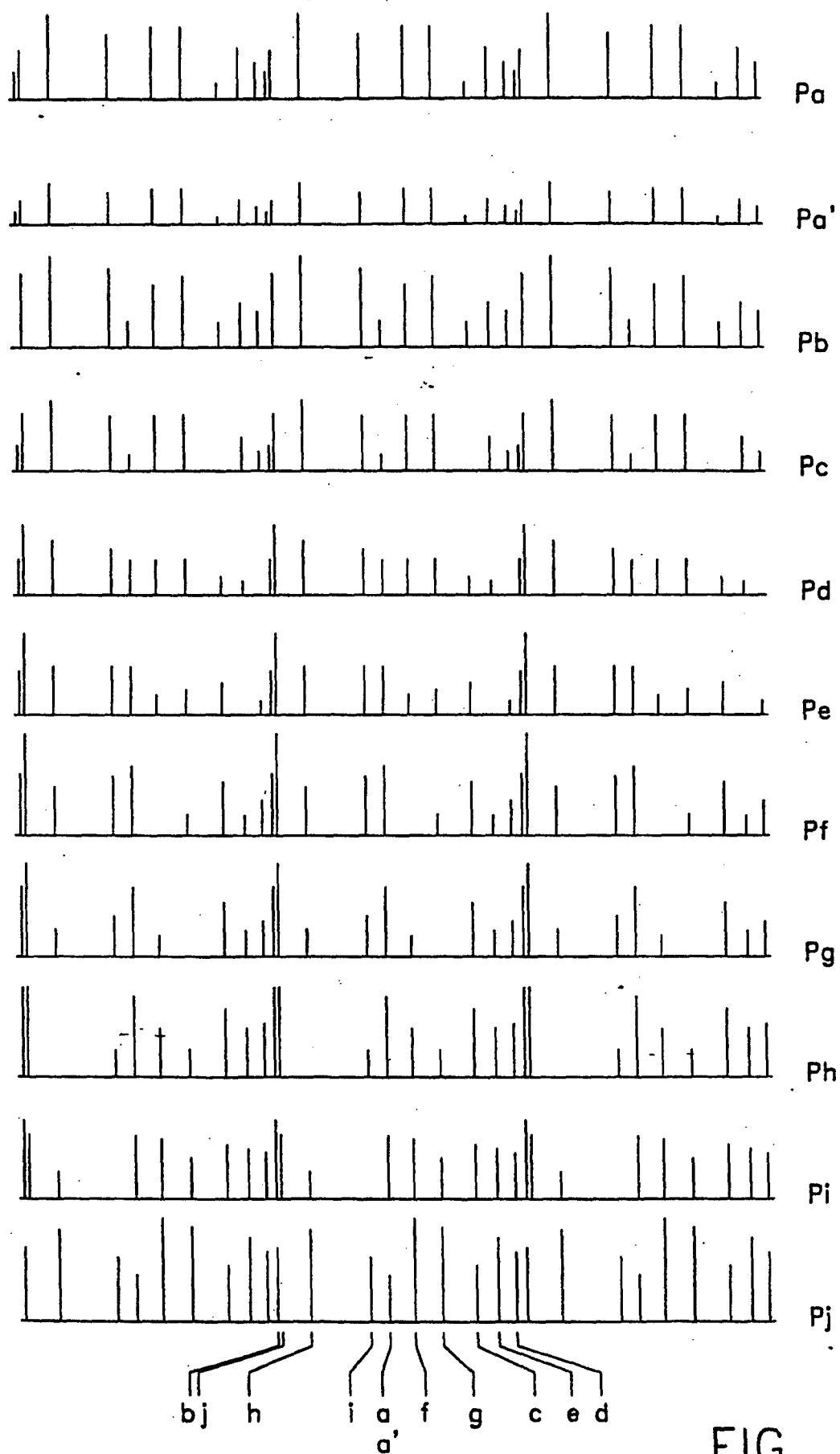


FIG. 21

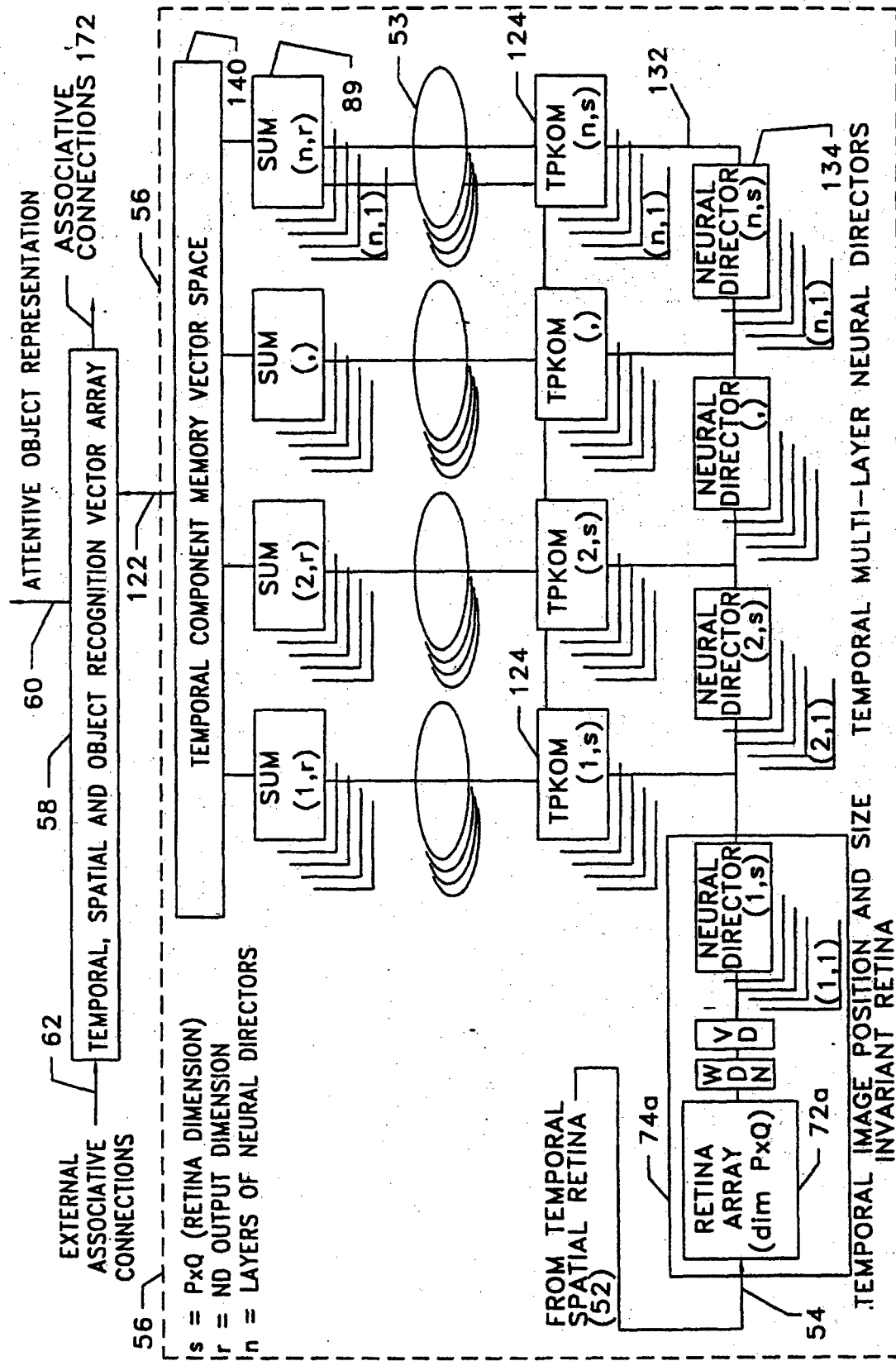


FIG. 22

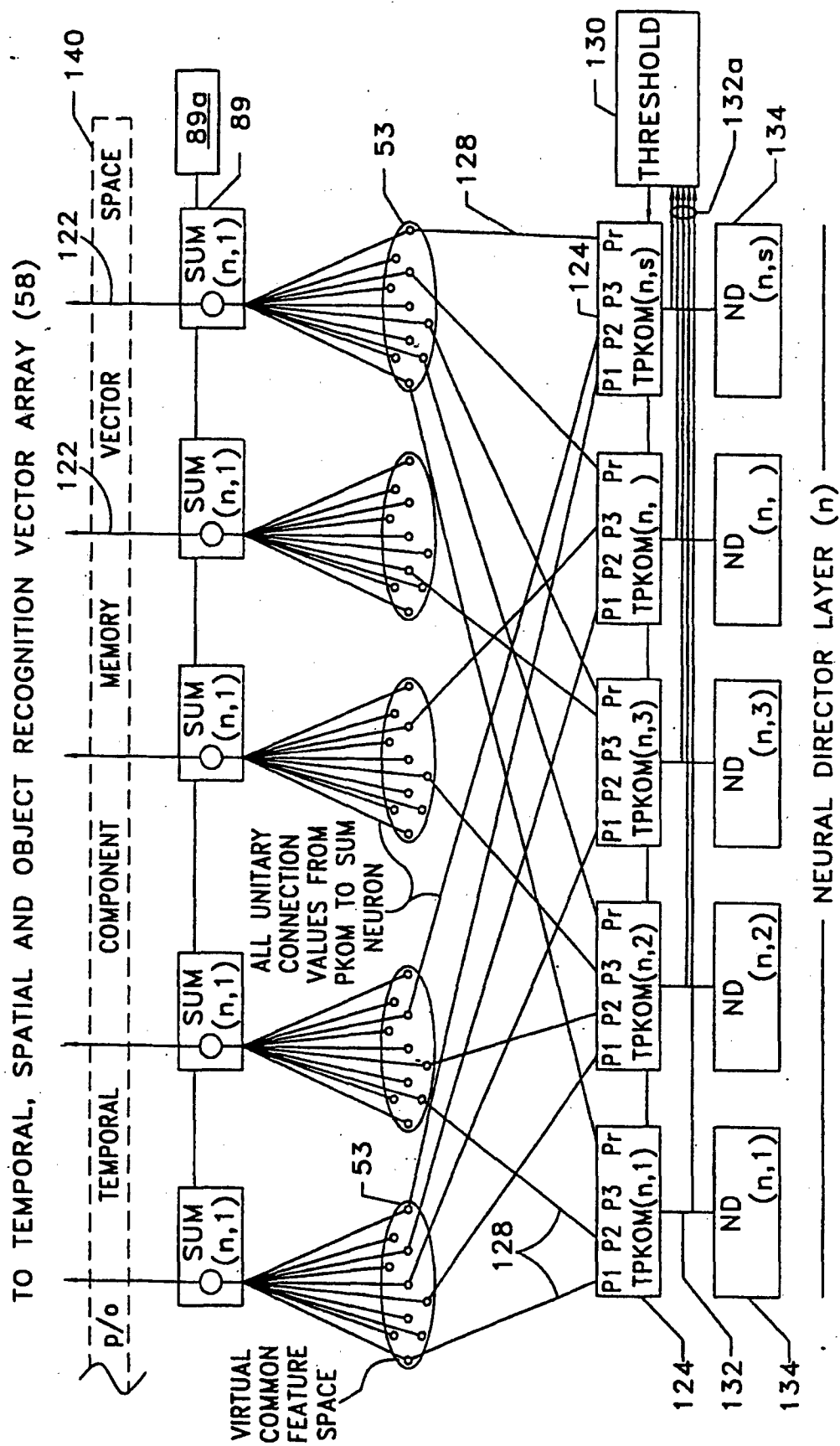
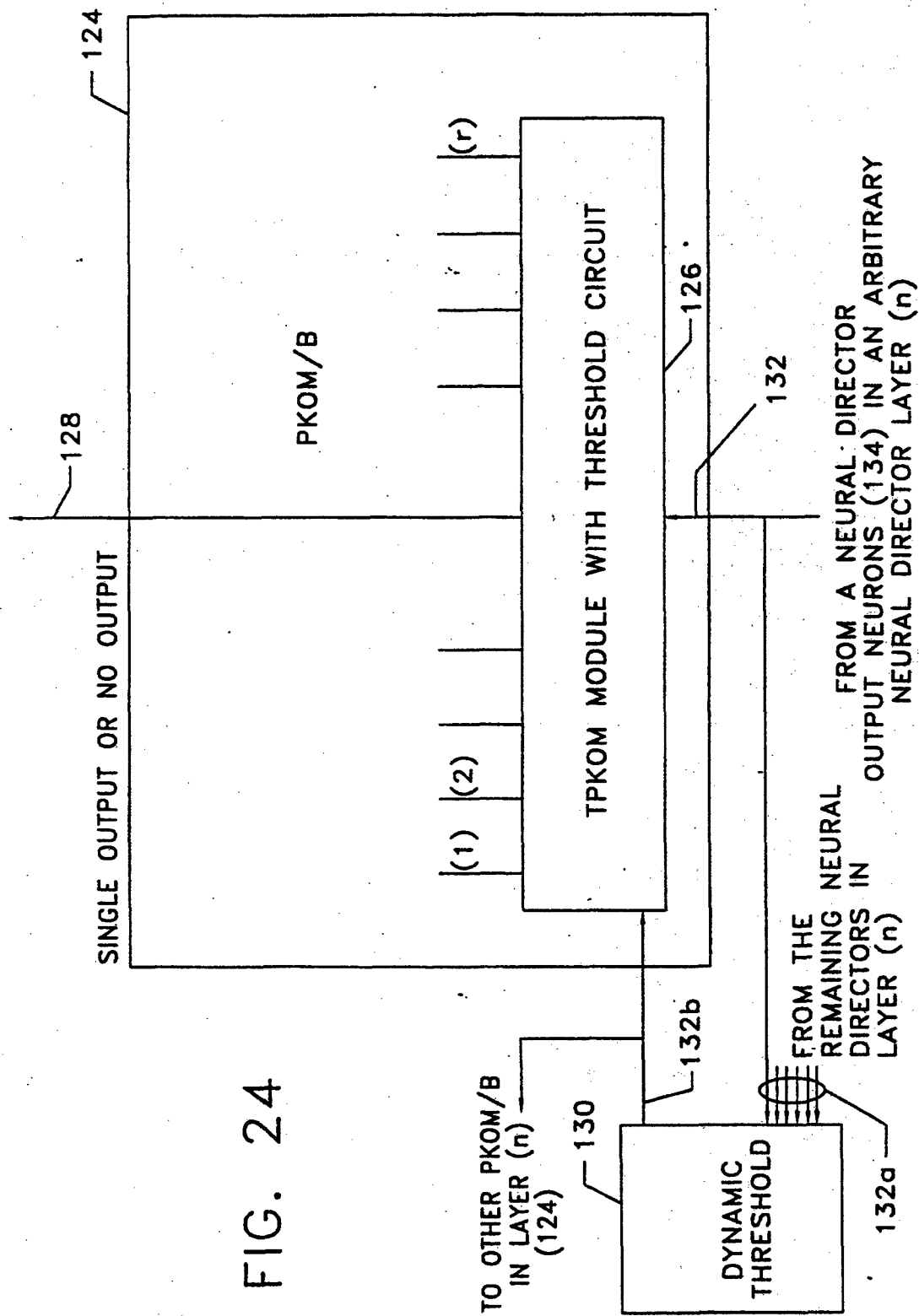
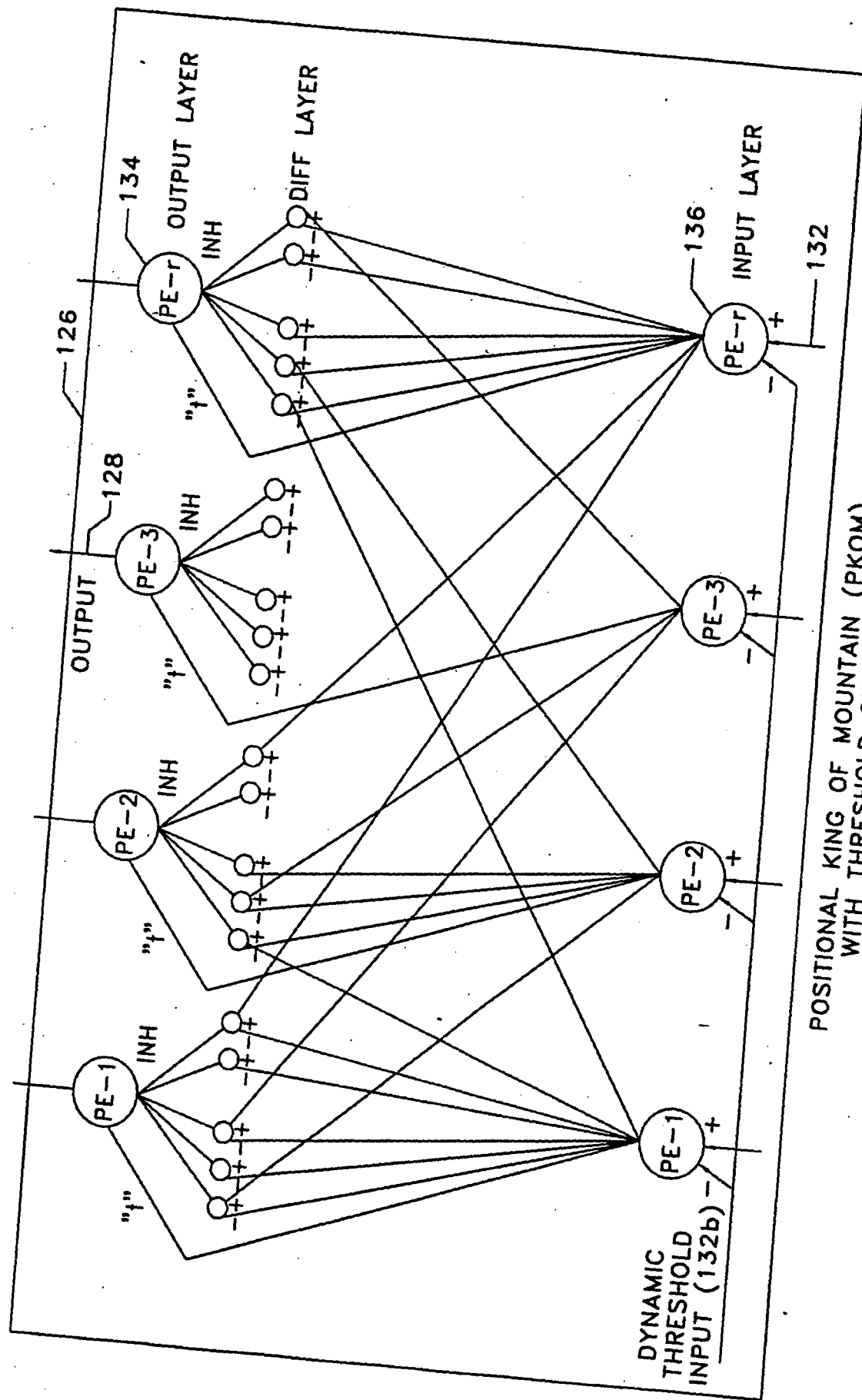


FIG. 23

FIG. 24





POSITIONAL KING OF MOUNTAIN (PKOM)
WITH THRESHOLD CIRCUIT

FIG. 25

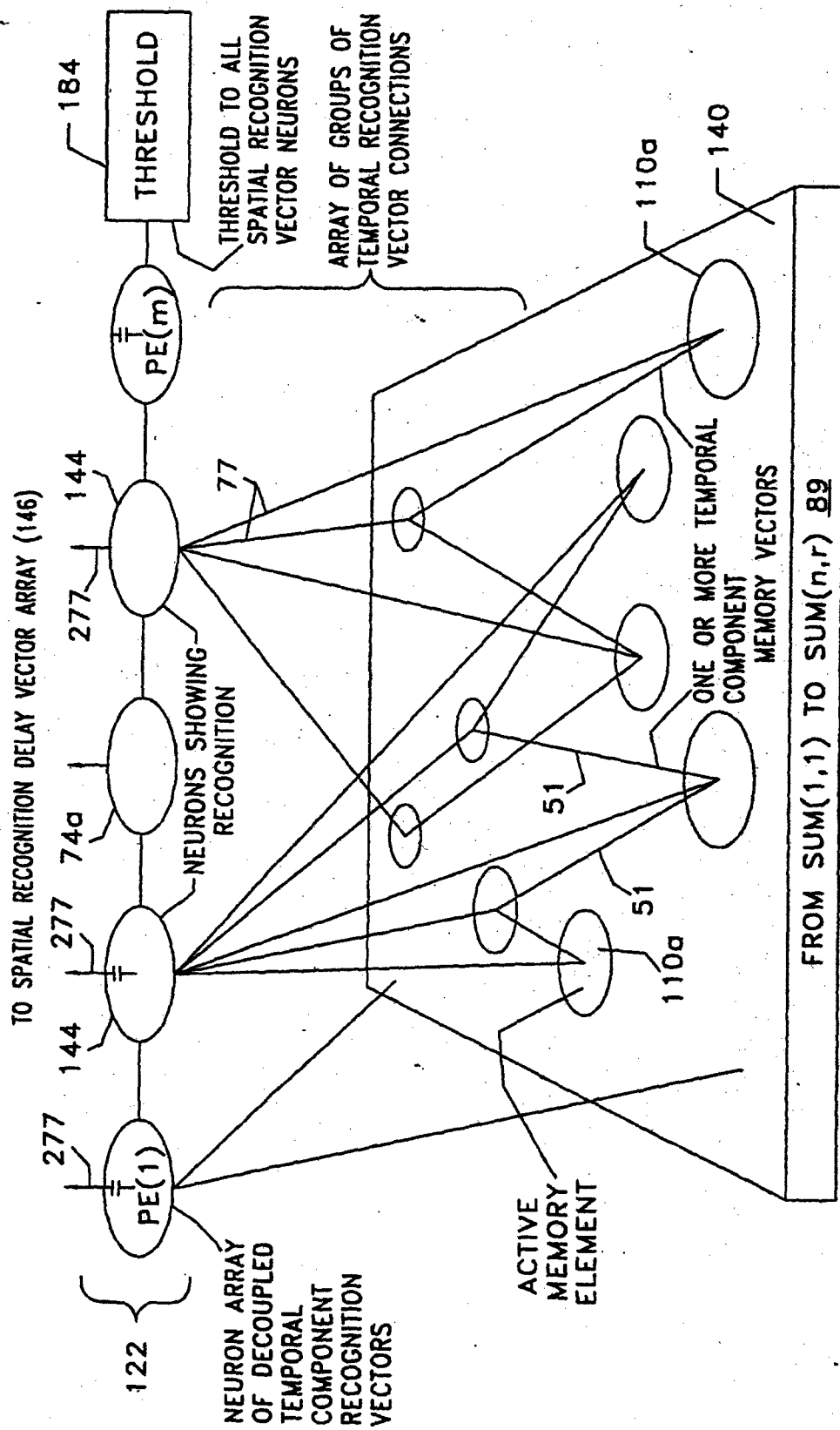
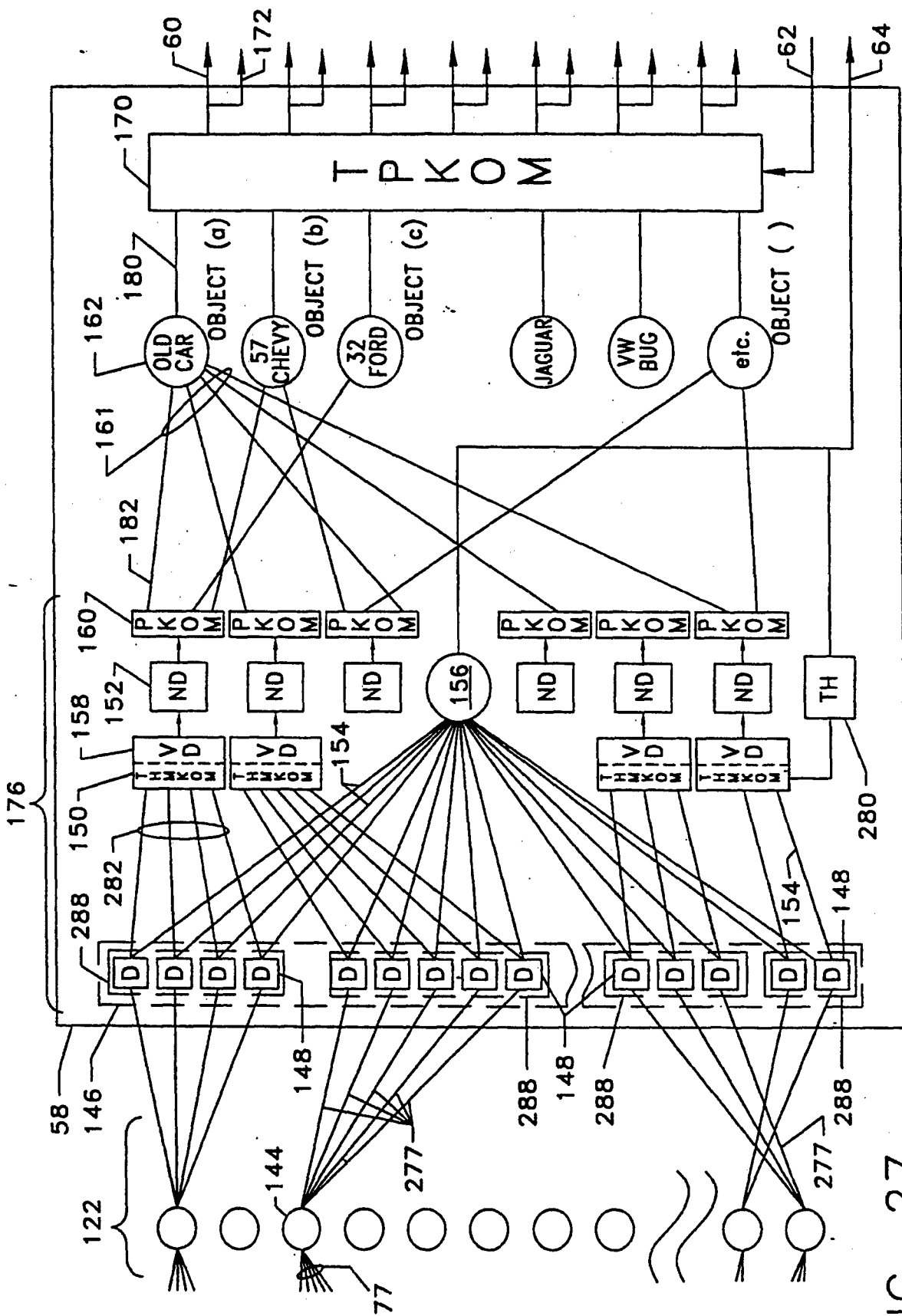


FIG. 26



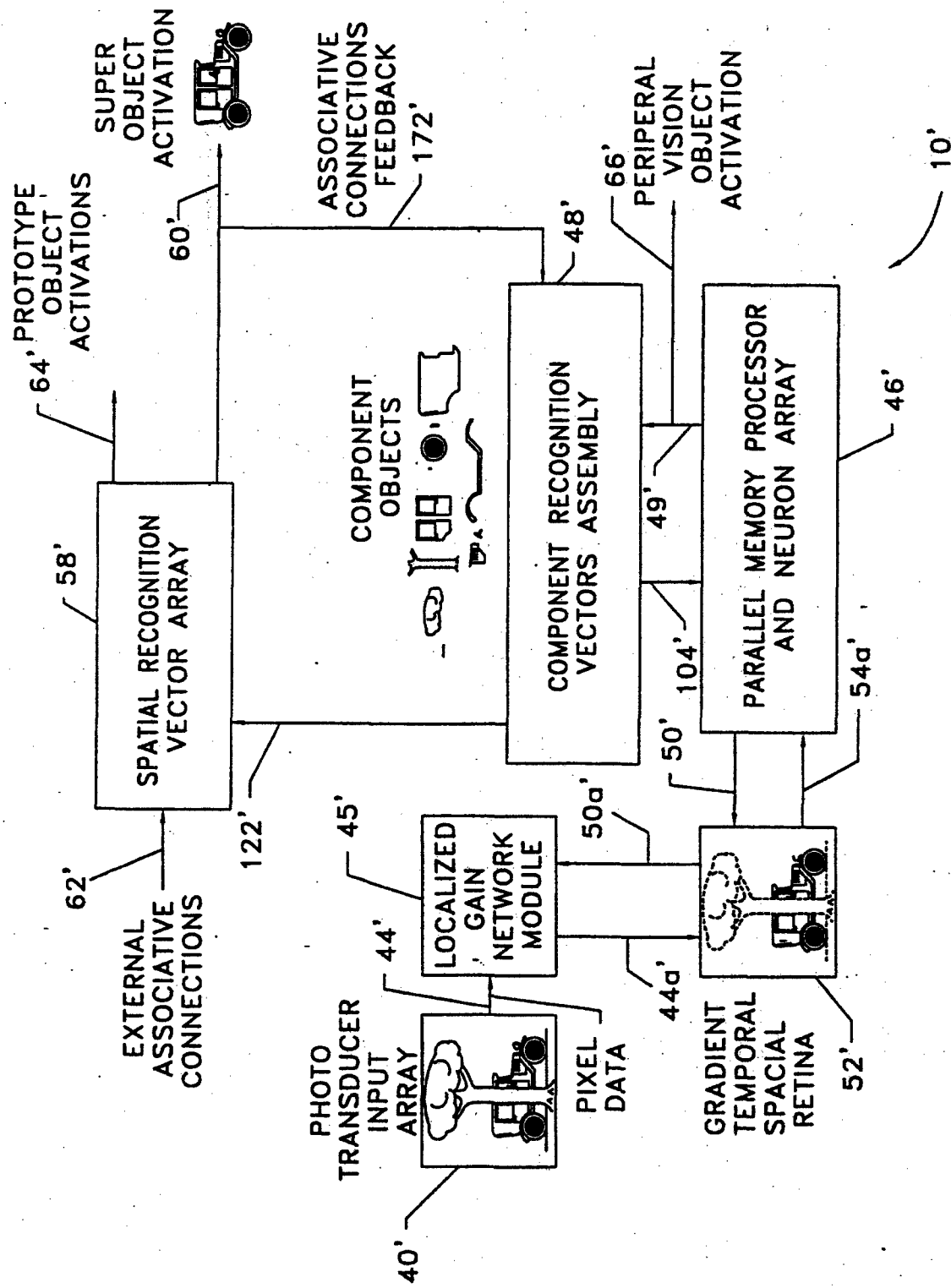


FIG. 28

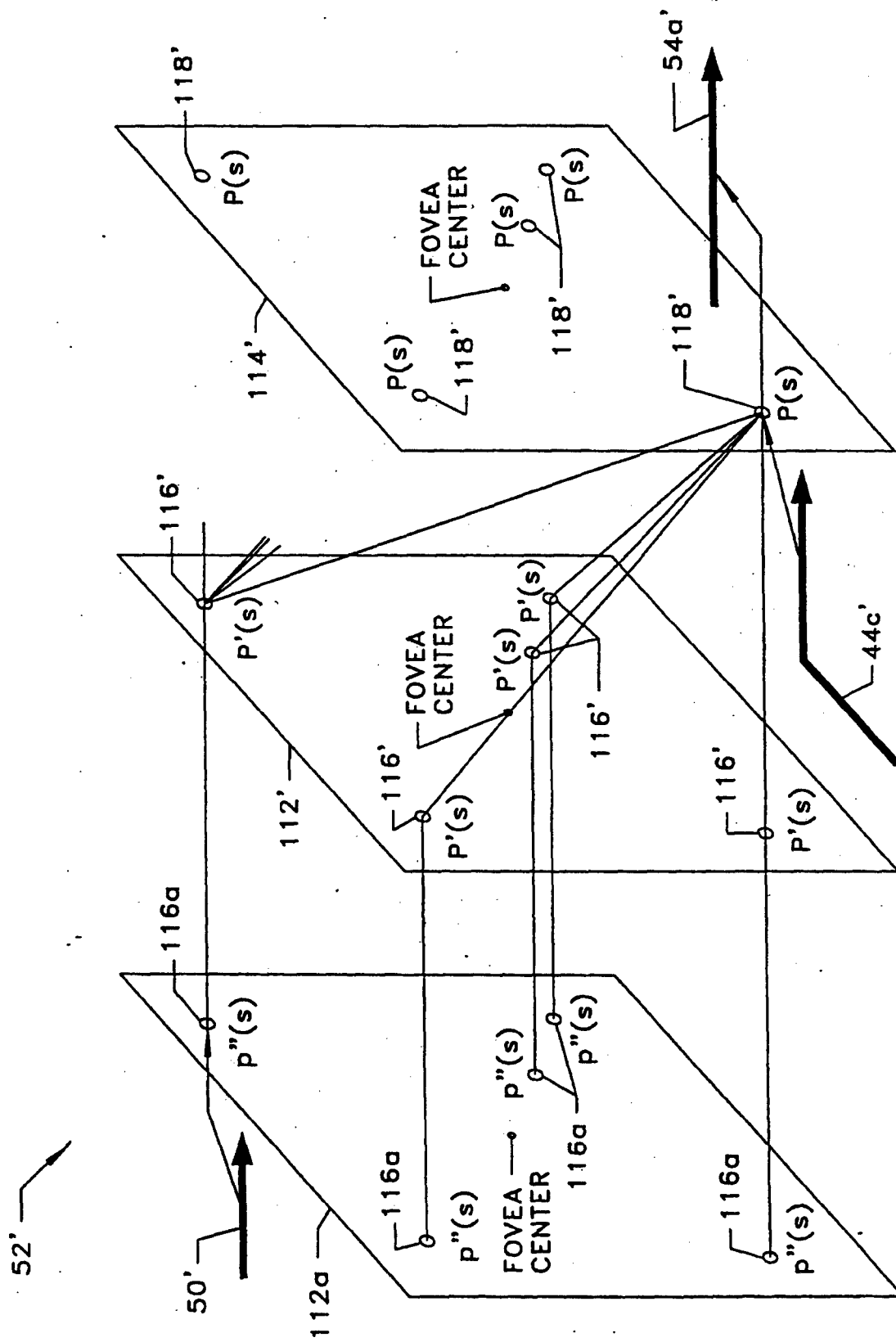


FIG. 29

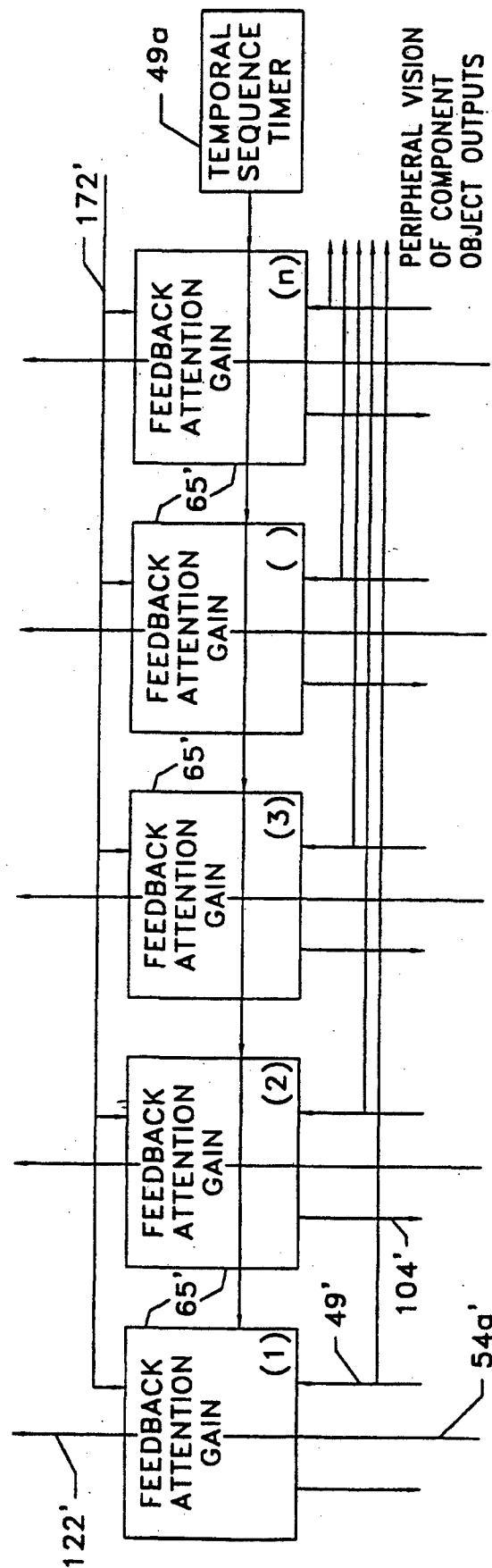


FIG. 30